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THESIS

SWARM OBSERVATIONS: IMPLEMENTING INTEGRATION THEORY TO UNDERSTAND AN OPPONENT SWARM

by

Anner Gaby Diukman

September 2012

Thesis Advisor:	Gary Langford
Second Reader:	John Osmundson

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13. ABSTRACT (maximum 200 words)

Swarm counter measure systems currently use enhanced weapons and sensor capabilities to address the threat of opponent swarms. However, there is a gap in current defense capabilities to counter swarm attacks, because brute force, or the enhancement of current defense systems by adding to defense capabilities are inadequate because of the inherent robustness, flexibility and adaptation of swarm attacks. Because of this, an overarching model is sought to understand the underlying command and control mechanism of an observed swarm threat, so that mechanisms that determine swarm behaviors can be understood. This will enable the development of countermeasures to counter swarms using specialized systems or tactics for certain behavior types. Integration theory provides an abstract model adequate throughout disparate swarm intelligence-domains (such as biology, computer algorithms, physics, and sociology). Integration theory, used with agent based modeling and analytical methods such as fractal dimensions, entropy, correlation and spatiotemporal structures, shows that it is possible to differentiate among the underlying C2 mechanisms by observing the swarm movement patterns. Adopting a swarm analytical observation approach is advised to promote the implementation of effective future countermeasures.

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SWARM OBSERVATIONS: IMPLEMENTING INTEGRATION THEORY TO UNDERSTAND AN OPPONENT SWARM

Anner G. Diukman
Captain, Israel Defense Forces
B.S., Hebrew University Jerusalem, 2005

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September 2012

Author: Anner G. Diukman

Approved by: Gary O. Langford
Thesis Advisor

John S. Osmundson
Second Reader

Clifford A. Whitcomb
Chair, Department of Systems Engineering

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ABSTRACT

Swarm counter measure systems currently use enhanced weapons and sensor capabilities to address the threat of opponent swarms. However, there is a gap in current defense capabilities to counter swarm attacks, because brute force, or the enhancement of current defense systems by adding to defense capabilities are inadequate because of the inherent robustness, flexibility and adaptation of swarm attacks. Because of this, an overarching model is sought to understand the underlying command and control mechanism of an observed swarm threat, so that mechanisms that determine swarm behaviors can be understood. This will enable the development of countermeasures to counter swarms using specialized systems or tactics for certain behavior types. Integration theory provides an abstract model adequate throughout disparate swarm intelligence-domains (such as biology, computer algorithms, physics, and sociology). Integration theory, used with agent based modeling and analytical methods such as fractal dimensions, entropy, correlation and spatiotemporal structures, shows that it is possible to differentiate among the underlying C2 mechanisms by observing the swarm movement patterns. Adopting a swarm analytical observation approach is advised to promote the implementation of effective future countermeasures.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABM	Agent Based Models
ACO	Ant Colony Optimization
CA	Cellular Automata
CAS	Complex Adaptive System
C2	Command and Control
EMMI	Energy, Material, Material wealth and Information
FIAC	Fast Inshore Attack Craft
GTM	Grounded Theory Method
HSI	Human Systems Integration
HVU	High Value Unit
LOS	Line Of Sight
MANA	Map Aware Non-uniform Automata
PSO	Particle Swarm Optimization
SA	Situational Awareness
SE	Systems Engineering
SNR	Signal to Noise Ratio
SO	Self Organization
STD	Standard Deviation
TSP	Travel Salesman Problem
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle

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EXECUTIVE SUMMARY

Current military tactics have recently started to use swarm concepts. Swarm attacks are robust, flexible, and adaptive by nature. There is gap in current defense capabilities to counter such swarm attacks. Due to the robustness (lack of single point failures) and relative ease of scaling up swarm numbers (with respect to cost and complexity), using brute force to enhance current defense systems may not be the correct approach. Mechanisms that determine swarm behaviors may make it possible for swarms to be countered if they enable the use of specialized systems or tactics for a certain behavior type. As swarms may be very inexpensive, they therefore create a need to obtain cost-effective defensive measures. Understanding swarm behaviors may reduce costs of defense and may even fully defeat swarm attacks. Insights gained from this initial research, may stimulate additional more expansive and definitive work in developing such a "behavioral" observation system.

This thesis aimed to contribute to the understanding of an opponent swarm in the following aspects:

- To enable faster, more appropriate responses to a swarm attack.
- To enable cost-effective swarm counter-measures to be utilized.
- To provide preliminary understanding of the aim of the swarm.
- To give appreciation of the type of command and control operative with the swarm.
- To give insights into possible statistical differences between different swarm types in given test cases.

Inspired by integration theory, an integrative model for the swarm was developed. The integrative meta-model was based on an abstract description of the swarm objects (agents, C2 unit, and environment) and processes (transfer of EMMI (energy, material, material wealth, and information)). This model had sufficient level of abstraction to be relevant to all swarm perspectives covered by the different domains in the literature review (e.g., swarms in biology, cybernetics, sociology, physics, and computer science).

After translation of the abstract swarm model to practical implementation in the Map Aware Non-Uniform Automata (MANA) agent-based simulation environment, MANA was used to explore different scenarios that included the following activities

- Rally – attraction of swarm agents to one another in space.
- Avoid – swarm avoidance of a perceived threat object / entity.
- Integration – swarm agents are capable of changing their local rule set in accordance to input stimuli.
- Triangulation – locating the physical location of a LOS C2 unit based on observed swarm movement patterns.

The analysis results showed the ability to differentiate the selected control mechanisms based on several methods:

- Swarm agents speed correlation measure.
- Formation of spatiotemporal structures (in space over time) with varying density and dispersion by agent positional data.
- Change in the swarm's spatial entropy measure over time.
- Change in the swarm's fractal dimension behavior over time.

A possible mapping method of these measures back to the underlying weighting preferences of the swarm agents is suggested for further study. In addition, the integrated swarm displayed a unique "shift phase" between behaviors which would help identify the presence of integration due to discontinuity in the system-measures derivative.

Lastly, triangulation of the swarm C2 source feasibility is displayed, with inherent limitations in accuracy. Initial accuracy improvement studies show dependence on:

- Number of swarm agents used for estimation.
- Ability to compensate for command lag through exploration of different time delays from recorded positional data.

This thesis concludes that the proposed observational approach would allow mapping of an observed behavior into a category (group) of rule sets (control schemes). This mapping of swarm control-mechanism categories would be established from the integrative model and would be categorized by their information source, interaction type

and level of integration. Additional knowledge such as the swarm's C2 unit location, and communication range constraints might be established by utilizing observed movement patterns data. It is suggested that further study of the proposed observational system would be conducted in order to contribute to a qualitative understanding of the opponent swarm, thus contributing to the selection and effectiveness of counter-measures.

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I. INTRODUCTION

Swarm intelligence is a growing domain of interest. Inspired originally from the field of social insects in biology, swarm intelligence is now a research topic in operations research, robotics and computer science. Swarm intelligence studies have proven that complex behaviors and problem solving capabilities can emerge from simple agent based rules. Swarming control algorithms are currently under research for unmanned vehicles applications. The robustness and adapting capabilities are of interest in the application of a swarm of unmanned vehicles for different tactical tasks.

Current military tactics have recently started to use swarm concepts. Swarm attacks are robust, flexible and adaptive by nature. There is a gap in current defense capabilities to counter such swarm attacks. Using brute force to enhance current defense systems may not be the correct approach. Mechanisms that determine swarm behaviors may be exploitable to counter swarms by utilizing specialized systems or tactics for a certain behavior type. Swarms may be very inexpensive and therefore create a need to obtain a cost-effective defensive measure. Understanding swarm behaviors may reduce costs of defense and may even fully defeat swarm attacks. Insights gained from this initial research, may stimulate additional more expansive and definitive work in developing such a "behavioral" observation system.

This thesis aims to contribute to the understanding of an opponent swarm in the following aspects in that it seeks to enable faster, more appropriate responses to a swarm attach, thus faster and more cost effective swarm counter measures; to provide a preliminary understanding of the aim of a swarm, and further appreciation of the type of command and control operative with the swarm, and to provide insights into possible statistical differences between different swarm types in given test cases.

The goal of this thesis is to gain insights into the ability of an external observer to understand the underlying control mechanism of an opponent swarm. In order to understand the C2 aspects of a tactical swarm, a cognitive meta-model of the swarm concept must first be established. The basis for this meta-model is integration theory

which helps facilitate our understanding of systems in general through the interactions and emergent properties of the objects and processes that constitute the overall system. The hypothesis of theory generation through observation of interactions is based on Radcliffe Brown's structural functionalism theory as explained in the review of scholarly research associated with the development of a meta-model.

To establish a broad basis for the comparative analysis, research conducted into the behaviors of swarms in different domains was performed. The following topics were surveyed:

- Swarms in social insects.
- Self-organization ingredients and characteristics.
- The definitions of different levels of autonomy
- Swarm approaches in cybernetics
- Abstract swarms in computer algorithms
- Implementation of swarms inspired by physics concepts
- Swarms in the domain of sociology, regarding crowd patterns, collective decision making and in organizations

In addition to surveying swarm behaviors in different settings, different system views and the perspectives of stakeholders interested in these topics were also collected and considered. Qualitative differentiation between centralized and autonomous swarms from the operator and agent perspectives was demonstrated with the use of the Taguchi loss function method.

Inspired by the concepts found in integration theory, an integrative model for use analyzing the swarm was developed. The integrative meta-model is based on an abstract description of the swarm objects (agents, C2 unit and environment) and processes (transfer of EMMI (energy, material, material wealth, and information)). This model had sufficient level of abstraction to be relevant to all the swarm perspectives covered by the different domains, as described in research associated with the topic of swarm behaviors.

The next step of the research required the translation of the abstract swarm model to practical implementation in the MANA agent-based simulation environment. A framework that translates control mechanisms into MANA is shown in Chapter VII.

After establishing the framework, MANA was used to explore different scenarios that included:

- Rally – attraction of swarm agents to one another in space.
- Avoid – swarm avoidance of a perceived threat object / entity.
- Integration – swarm agents are capable of changing their local rule set in accordance to input stimuli.
- Triangulation – locating the physical location of a LOS C2 unit based on observed swarm movement patterns.

The first two scenarios compared different control mechanisms based on local, global and hybrid information sources (i.e., agent-based information, shared information source or a combination of both). The integration scenario explored the unique characteristics displayed by the movement patterns of a swarm capable of changing its internal rule set. The fourth scenario displayed the feasibility of locating a short range command source based on observed changes in swarm agents' moving patterns.

The analysis results showed the ability to differentiate the selected control mechanisms based on several methods:

- Swarm agents speed correlation measure.
- Formation of spatiotemporal structures (in space over time) with varying density and dispersion by agent positional data.
- Change in the swarm's spatial entropy measure over time.
- Change in the swarm's fractal dimension behavior over time.

A possible mapping method of these measures back to the underlying weighting preferences of the swarm agents is suggested for further study. In addition, the integrated swarm displayed a unique "shift phase" between behaviors which would help identify the presence of integration due to discontinuity in the system-measures derivative.

Lastly, triangulation of the swarm C2 source feasibility is displayed, with inherent accuracy limitations. Initial accuracy improvement studies show dependence on:

- Number of swarm agents used for estimation.
- Ability to compensate for command lag through exploration of different time delays from recorded positional data.

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II. BACKGROUND

The goal of this thesis is to gain insights into the ability of an external observer to understand the underlying control mechanism of an opponent swarm. In order to understand the C2 aspects of a tactical swarm, a cognitive meta-model of the swarm concept must first be established. The basis for this meta-model is integration theory which helps facilitate our understanding of systems in general through the interactions and emergent properties of the objects and processes that constitute the overall system. The hypothesis of theory generation through observation of interactions is based on Radcliffe Brown's structural functionalism theory as explained in the literature review.

By using grounded theory methodology, emphasizing theory formulation from observed data, categories emerged from the data (be it literature or simulation in this thesis), through constant and iterative comparative analysis.

To establish a broad basis for the comparative analysis, an extensive literature review of swarms in different domains had to be performed. The literature review starts with the initial inspiration for the swarm concept - social insects. The review continued to investigate self-organization ingredients and characteristics. A review of autonomous levels definitions and the advantages of a swarm approach in cybernetics was covered. The implementation of abstract swarms in computer algorithms was shown through the well-established Ant Colony and Particle Swarm optimization algorithms. Much like the biological-inspired swarm approach, the review studied the implementation of swarms inspired by physics concepts (dubbed *Physicomimetics*) such as potential, entropy and fractal dimensions. Lastly and most importantly, the review studied swarms in the domain of sociology, regarding crowd patterns, collective decision making and organizations.

The literature review made a critical contribution to the establishment of the swarm functional decomposition and loss functions. The validation of the integrative meta-model for the swarm was possible by confirming the model abstraction level was sufficient to describe all swarm domains covered in the literature review.

Lastly, the literature review inspired the selection of scenarios and control mechanisms test cases for the MANA simulation. The system approach to the analysis of the "observed" swarm data was influenced by the literature as well (e.g., fractal dimensions, spatial entropy, spatiotemporal structures and field potentials).

III. PROBLEM DEFINITION

A. PROBLEM STATEMENT

Swarms are inherently adaptive, robust and flexible. Utilization of swarms in offensive tactics is becoming more prominent. Current defense systems lack the effective capability to counter swarm offensives. Simply enhancing defense systems' capabilities may prove insufficient. By understanding the underlying swarm behavior, specialized systems and tactics can be used to counter the swarm. Cost effective counter-measures are required due to the relative ease of creating numerous swarm agents. Better understanding of underlying swarm mechanisms can potentially reduce costs of defense and may even render a swarm ineffective. Hopefully, this research may encourage more thought into the development of such a swarm observation system.

B. RESEARCH QUESTION

1. Main Question

What information can an external observer viewing all the agents of the swarm infer about their underlying behavioral characteristics? The scope of this question focused on mapping different information flow schemes (i.e., centralized vs. distributed) throughout the swarm to related movement patterns.

2. Subsidiary Questions

- What the relevant behavioral characteristics of a swarm are as defined in different domains (i.e., biology, cybernetics, sociology and physics)?
- What are the different system views of the swarm?
- What different stakeholders' perspectives exist of a swarm?
- From a tactical defensive perspective, is there any importance to have a qualitative model for an opponent swarm? If so, how can it be used?
- How does information flow affect the swarm movement patterns?
- Can the different patterns be statistically distinguishable?

3. Questions for Further Research

- Will an artificial "observation" system be able to notice the differences in these complex behaviors? (i.e., with no man in the loop)
- Can the complex emergent behavior be mapped back to a single local rule set? Or are there many possible input rule sets that result in the same complex behavior?

C. RESEARCH SCOPE

The focuses of this research are the command and control aspects of a tactical swarm. The research scope of this thesis is limited to observation and analysis of artificial swarm movement patterns and their correlation to different underlying control mechanisms. A high level integrative model of the swarm is developed in light of a needed mapping framework of such control mechanisms to information flow schemes in the tactical swarm. This research does not aim to develop new swarm counter-measures or tactics, but rather suggest the feasibility of an observational approach to distinguish different swarm control mechanisms.

D. CONTRIBUTION OF THE RESEARCH

This thesis aims to contribute to the understanding of an opponent swarm in the following aspects:

- Enabling faster, more appropriate response to a swarm attack.
- Enabling cost-effective swarm counter-measures that can be utilized.
- Offer a preliminary understanding of the aim of the swarm.
- Create appreciation of the type of command and control operative with the swarm.
- Provide insights into possible statistical differences between different swarm types in given test cases.

E. RESEARCH HYPOTHESIS

The research hypothesis for this thesis was that it would be possible to develop a general model for a swarm based on the integration of objects and processes. This generalized form would be the only way to capture different elements (abstract / artificial / organic) that comprise the swarm and their different forms of C2.

In addition, it was hypothesized that it would be impossible to know the exact rule set that resulted in the observed behavior. Mathematically this has to do with the notion of irreversible functions –

- **A single rule set can result in multiple observed behaviors** (this is similar to genotype and phenotype, depending on external conditions.)
- **Different rule sets may result in the same observed behavior,** given certain environmental conditions. (e.g., where there is an attempt to distinguish speed correlation behavior in the case of a large agent's sensor range vs. global information source based on multiple agents).

Regarding both causes, even if theoretically the rule-set-function was reversible, in reality, the observer does not have accurate knowledge of initial and final environmental conditions that led to the outcome behavior. Given this inherent uncertainty, some differentiation capability is lost.

Despite the previous point, it was hypothesized that it would be possible to map an observed behavior into a category (group) of rule sets (control schemes). Although not specific, it would still contribute to a qualitative understanding of the opponent swarm. Under this general definition, a categorization dichotomy system of control schemes would be possible. Swarm control-mechanism categories would be established from the integrative model and would be categorized by their information source, interaction type and level of integration.

F. ASSUMPTIONS AND APPLICABILITY

This thesis relies on Radcliffe's concept of generating theory through comparative analysis of observable interactions between individuals (see literature review). The assumption or extension of this concept is in its application to human surrogates, man-made objects (swarm agents), instead of human beings. So by observing the interactions between these objects, we are able to formulate a theory regarding the underlying human intent projected through them.

An additional assumption made in the agent based model scenarios of a swarm is that the swarm is built of homogenous agents. This is a lenient assumption, made in order to facilitate initial research. In reality, tactical swarms may include heterogeneous agents.

The last key assumption made is that the observer (or observation system) is able to obtain and record all swarm agents' positions in time over a specified area of interest. Errors in recorded position data were not considered as part of the research scope.

G. RESEARCH APPROACH

The research approach for this thesis is divided into two basic approaches to the swarm. The first is to approach the swarm as individual agents. The second is to approach the swarm as a system. These two approaches are reflected throughout the research in the guiding theories, selected methods and tools of research. These approaches can be seen in in the literature review, the integrative swarm model and the agent-based simulation analysis. By viewing the swarm as individual agents, we focus on interactions between agents and resulting changes in individual traits to facilitate theory generation (based on Radcliffe's structural functionalism). By viewing the swarm as a system, we focus on macroscopic swarm views for the research. Both approaches rely on integration theory as a meta-model to facilitate the individual and system cognitive-models of the swarm.

H. RESEARCH METHODS

As discussed previously, the underlying theories for the research were integration theory and Radcliff's "structural functionalism" (RADCLIFFE-BROWN, 1935). The practical method used for theory generation was based on the Grounded Theory Method (GTM) formulated by Glaser and Strauss in (Glaser & Strauss, 1967). GTM formulates an approach of how to develop theory based on different sources of qualitative data. It relies on theory forming by induction from data observed (without prejudice or previous literature bias). Interpretation of data becomes the theory. Based on Radcliffe's theory and the use of GTM, local observations can be generalized through comparative analysis of different test cases and induction into a generalized theory of underlying control mechanisms.

The GTM comparative analysis was used in the literature review research. The literature review aims to cover as many swarm perspectives possible in different domains in order to establish the broadest basis possible for comparative perspectives analysis.

Comparative analysis was used in the analysis of different control mechanisms in the agent based model simulation. For example, by comparing the different outcomes of a statistical measurement for different swarm-information sources, a theory regarding the entire spectrum of information sources could be suggested.

Considering the two basic approaches to the swarm as individual agents and a system, different analysis methods were used, as shown in Table 1:

Approach	**Swarm as individual agents**	**Swarm as a system**
Methods used	GTM	GTM
	-	System views
	-	Stakeholders perspectives
	Functional decomposition for a swarm agent	Functional decomposition for the swarm system
	Agent speed standard deviation for autonomous threshold	Taguchi loss functions for different control mechanisms
	Agents velocities correlation	Spatiotemporal structures
	-	Fractal dimensions
	Agents positions correlation	Entropy
	Agent movement pattern based triangulation	Field potential

Table 1. Research methods under different research approaches

The tools used in this research were the MANA agent based modeling environment and the MATLAB software environment. MANA was used to explore different scenarios and control mechanisms. The raw agents-positions data recorded from MANA were then imported into the MATLAB environment. MATLAB was then used to perform analysis using the various statistical and physics based methods described in Chapter VII.

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IV. KEY DEFINITIONS

The following section includes definitions to key terms used in this thesis. The terms are defined with respect to their relevance and use in integration theory which is the basis meta-model for the proposed swarm integrative model in this thesis. The definitions in Table 2 were taken from (Langford, Engineering Systems Integration: Theory, Metrics and Methods, 2012).

Word (noun)	**Relevance to Integration**
Action	An action is the release or receipt of something due to the enactment of a mechanism.
Attribute	Attribute is a measure and measurement, configuration and structure, and constraint (e.g., time, cost, and scope), performance and loss due to achieving the performances of a function.
Behavior	A behavior is describable in terms of observed reactions to influences of energy, matter, material wealth, or information. A behavior is the movement of objects by processes; processes that result in objects; objects interacting with other objects.
Causality	The sequence of events we term causality – event by event. Causality requires that the relation between two objects be modeled as the change in the sending object, the change in the receiving object, and the context of both the sending and receiving objects. Causal events have both provenance and pertinent specificity. Causality is formed from the modal threads of events leading to the proximate events (nearby in space and time) from which the conditions are stipulated to select the necessary and sufficient events.
Cohesion	The manner in and degree to which the objects or processes relate to each other.
Complexity	Complexity results from emergent properties of integrated objects, number and types of processes, and the number, types, and frequency of interactions between and within processes. Complexity can be seen as relative to the level of abstraction in which one views two objects.
Coupling	The degree of dependency between objects or between processes.
Deduction	An inference based on a principle, rule, or process.
Emergence	Any effect that produces a change in intrinsic properties, traits or attributes, that results by combining objects through the interactions of objects with EMMI. Emergence is due to the traits of an object or objects, process or processes.

Word (noun)	**Relevance to Integration**
Framework	A framework is the logics and consistency of method for a group of frames. The structure of concepts and narrative is termed a framework. A framework is characterized by its (1) consistency of logic, (2) continuity of method, (3) applicability across disciplines and fields involved in the frames, (4) scalable from the inter-domain's micro to macro instances and events, and (5) showing the requisite capaciousness to convey the needs of the scope of intentions that are inherent in its needs. Most importantly, the framework maintains focus on the eventual goal of describing a definitive theory of systems engineering.
Function	A function is defined as an action that is realized when objects interact. Specifically, the exchange of EMMI between two objects and satisfaction of the interface boundary conditions creates a function that did not exist before the connection. A function is described relative to a particular stakeholder's perspective. A function is the essence of interaction between two objects; and for integration, a function is a structural property of the relations between objects. A function is the result of the interaction or integration of two objects. A function manifests itself as a trait of interaction. A function provides for a use.
Induction	The logic of deriving a general law from an observation, perspective, measurement theory, and causalities framework. Induction assumes that (1) knowledge can be represented by rules that govern conditions, (2) rules are based on current and future states (suggesting causality is pluralistic), (3) rules are defined and enacted similarly in hierarchical or heterarchical structures, (4) subsets and supersets of objects or processes identify with the higher levels (in hierarchical thinking) and with primary reference objects and processes (in heterarchical thinking), (5) synchronic and diachronic rules promote superordinate relations, (6) interactions between objects that are of inconsistent frequency or are barely over thresholds necessary to activate mechanisms result in measurable outputs, (7) two classes of mechanism are possible – those that revise parameters and those that generate plausibility and rules, (8) mechanisms require interactions that lie within range of the parameters that control the mechanisms to result in measureable output, and (9) a depth and breadth of knowledge associated with actions and events, processes and activities are structured within frames that are consistent with the causalities framework (or integration framework). Langford's definition was extracted from and inspired by Holland, Holyoak, Nisbett, and Thagard (Holland, Holyoak, Nisbett, & Thagard, 1986).

Word (noun)	Relevance to Integration
Integration	*Integration is the unification of the objects through their interactions of energy, matter, material wealth, and information to provide system-level functionalities and performances.* Integration is a coalesce of objects, interacting in perhaps unpredictable ways. Integration is the combining of a systematic series of actions that take place in a definite manner, directed to bring about a particular interaction between objects and sets of objects. Integration is the method of setting up or by chance satisfying the conditions that lead to a set of objects we refer to as a system. Integration is a collaborative, value enhancing approach to demonstrating functionalities and performances of products and services. Integration is a method that facilitates outcomes that are beyond what an individual object can do either individually or by a number of objects acting independently, i.e., makes things happen that would otherwise not happen. Integration requires the structures of knowledge, the benefit of information, and meaningful data to determine the alternative ways in which to integrate a product or service. Langford also cites: Integration is defined variously as a unifying process (Kirk, Raven, & Schofield, 2009), the progressive linking of system components to merge functional characteristics into an interoperable system (Haskins, 2007), the whole is greater than the sum of its parts.
Interaction	Interaction is defined as the transfer of EMMI. Interaction is characterized by the transfer of something from one object (sender) to another object (receiver).
Loss	Loss is the relative, quantifiable difference in EMMI between the performance of a function at its target value and that measurement at any other value of performance. Loss can be thought of in terms of a generalized loss function that attributes EMMI losses to deviations from a target performance value; and as a result of not having a target performance value (meaning that a function was not provided or available for use and therefore had no performance value).
Mechanism	Mechanisms are the means by which objects and processes change. The effect of a mechanism is to transform an input EMMI into an output EMMI. A mechanism is that which operates in the context of forces.
Model	A model is a relation or set of relations between variables that are representative of an object or process (termed the objective part of the model). A model is based on a value or a set of values and a principle or set of principles that form the (subjective) basis for the relations making up the objective part of the model.

Word (noun)	Relevance to Integration
Object	We commonly think of an object as a fundamental element, entity, or representation. It may be atomic or an aggregation of entities. Objects are or represent material structures, material wealth, and information. From these physical entities comes energy or matter. Objects can be physical or abstract (e.g., intellectual). Objects may be conceptual, phenomenological, or ideological. Objects may be comprised of other objects, each of which is related by interactions. Objects can be ordinary or elemental. Objects have boundaries.
Process	A process can be articulated as a systematic pattern, a coordinated set of procedures, tasks, activities, or acts that result from the conversion of inputs into outputs. Process is the amalgamation of activities and tools that combine ideas. A process requires all things that are both necessary and sufficient to accomplish or achieve an intended output. Processes are comparable to other processes, subjectively. From an integration perspective, processes guide the work.
Property	A property is embodied in an object that is physical *or* represents something that is physical. A property can be real (physical or material) or intellectual (conceptual, nonphysical, or intangible). A physical property of matter is mass. Intellectual property is a representation of real, physical property, such as software (which represents a process that is enacted through physical objects.
Trait	A trait is the nexus of the property along with its conditions that distinguishes it from other traits.

Table 2. Key terms definitions. From (Langford, Engineering Systems Integration: Theory, Metrics and Methods, 2012)

V. LITERATURE REVIEW

A. GROUNDED THEORY METHOD

1. What is Grounded Theory?

Grounded theory method (GTM) was formulated by Glaser and Strauss in 1967 in their book *The Discovery of Grounded Theory*. It is one of the more popular research methods in social sciences. It is used in systems engineering and information systems research because of the social aspects of both these fields.

GTM formulates an approach of how to develop theory based on different sources of qualitative data. It relies on theory forming by induction from data observed (without prejudice or previous literature bias). Interpretation of data becomes the theory. The data leads the researcher in a repeatable manner to develop the theory (Glaser & Strauss, 1967). The repeatability is achievable within a paradigm. The theory is not developed from independent "logical" thinking or deduction. The aim is to discover the theory within the data and not to test a hypothesis. Glaser defines two main criteria to evaluate the suitability of the emerging theory: 1) how well the theory fits the situation described and 2) whether it helps people in the situation to make sense of their experience and to manage it better.

2. Grounded Theory and Literature

Literature is treated the same way as any other data source (it has no priority over observation or experiments). Glaser even states, based on years of using grounded theory, that a researcher should consider not reading literature on the immediate subject beforehand to prevent himself from becoming biased in his noting and theory generation. According to (Edwards, 2010):

> Although most GTM researchers emphasize working from a minimal theoretical basis (Johnston et al., 2002), applying GTM correctly does not require entering the research without any prior knowledge and experience

> as long as the researcher is aware of this fact (Suddaby, 2006). Following this advice, Manuj and Mentzer (2008) wrote down their understanding of existing theory beforehand for reference as a way of consciously reflecting on it and trying to avoid imposing it directly on the data.

The approach in this thesis will be to refer to the literature to form a foundation view for the research. It is desirable to have the broadest view of relevant literature domains while keeping in mind the continual need to compare the literature theories with the emergent theory from the data.

3. Grounded Theory Process

Theory generation process in GTM involves several different steps (Glaser & Strauss, 1967):

- Data collection – from literature, discussion, interviews, experiments.
- Note-Taking – while collecting data the researcher writes down observation points that come to mind for later recovery and coding.
- Coding – coding involves several steps. First of all constant comparative analysis of the notes or observations taken. What commonalities are there? What differences? The previously identified commonalities are new categories for our theory. These categories may have several properties or sub-categories. A category that has the highest frequency and connections to other categories becomes the core-category. The researcher continues to identify connections between categories until saturation occurs (i.e., additional data does not develop the category any further). The researcher broadens his sample data by theoretical sampling. That is, actively pursuing data that adds diversity to the sample and understanding according to our previous theory discoveries.
- Memoing – taking memos to self is one of the more important steps of the process. it is done throughout the research and involves writing down any insight, thought and hypothesis that comes up in the process. these memos will become the basis for later theory formulation.
- Sorting – this step groups memos with similar categories and organizes them to reflect their relationships.
- Writing the thesis.

B. STRUCTURAL FUNCTIONALISM

In his article “On the Concept of Function in Social Science” (RADCLIFFE-BROWN, 1935), Radcliffe Brown describes how the concept of function in human

societies is based on an analogy between social life and organic life. The cells in an organism are not arranged as an aggregate in relation to one another but as an *integrated* whole. The organism has structure (of its elements and their relationships) but it is not the structure. By continuity of this structure the elements may change (e.g., replaced) but the organism continues. The life process (and its analogy, the social process) consist of the *activities and interactions* of the constituent units of the (social) system. To preserve social life - the social structure's functionality must be preserved.

After defining the concept of function above, Radcliffe continues to state that there are three problems to answer in the systematic investigation of social life:

- Social morphology – what types of social structures exist? How do they differ? How should they be classified?
- Social physiology - How do social structures function?
- Social development - How do new social structures come into existence?

Radcliffe points out several crucial differences between the organic and social analogy:

- The social life can only be *observed* by its functionality. Relationships can only be viewed in the context of the activities in which the relationships are functioning.
- Social life can change its structure over time (organic cannot).

A "function" by this definition is the partial contribution of an activity to the whole which it is part of. The social system has functional unity, which means its parts have internal consistency (they do not create unresolvable conflicts).

Radcliffe clarifies in his paper that this new definition of "social function" is a working hypothesis and that it does not require everything in the life of a social system to have a function, instead just the assumption that it may have one.

Radcliffe argues that social anthropology has to generate generalized theories (or laws) across societies. Thus, he endorses comparative generalizations; much like comparative analysis in GTM's coding process.

This thesis relies on Radcliffe's concept of generating theory through comparative analysis of observable interactions between individuals. The extension of this concept is in its application to man-made objects (swarm agents) instead of human beings. So by

observing the interactions between these objects we are able to formulate a theory regarding the underlying human intent projected through them. Based on Radcliffe's theory and the use of GTM local observations can be generalized through comparative analysis of different test cases and induction into a generalized theory of underlying control mechanisms.

C. SWARM INSPIRATION FROM SOCIAL INSECTS

Social insects such as bees, wasps, ants and termites have fascinated researchers for years. One such early example is *The Life of the White Ants* written by (Maeterlinck, 1927). The individual insect in the colony seems to be operating on its own yet the colony seems to have method and order that results in the actualization (and appearance) of organization. The integration of all activities doesn't seem to have any central control or supervision (Bonabeau, Dorigo, & Theraulaz, 1999, p. 1).

Leafcutter ants forage leaves hundreds of meters from the nest and are observed to have columns of ants transporting leaves. These movements appear orderly. Army ants perform raids involving hundreds of thousands individual ants. These raids are arranged with clear "front lines" and highways connecting them with the nest.

Insect colonies display what can be interpreted as division of labor. According to (Bonabeau, Dorigo, & Theraulaz, 1999, p. 2) different tasks are allocated between individuals deferring by morphology, age, or chance. This method is believed to be more efficient than sequential tasking performed by unspecialized workers. Studies have shown that removal of one class of workers will stimulate replacement by workers from a different class (Wilson, 1984).

Honey bees form columns to regulate heat inside the nest. This action helps in shaping the wax combs which incorporate the nest. Termites and wasps are known to build intricate nest structures with different specialized chambers (i.e., a form of physical and functional architecture).

A single insect has the capability to process sensor stimuli, interact with other insects and change its behavior accordingly. Despite these significant capabilities, the overall complexity of cooperation cannot be explained without better understanding of

the underlying interactions and mechanisms at play. Some complex properties such as task allocation can be explained by genetic code, but others are explained through the concept of self-organization (SO). This concept will be elaborated on in the next section, but for a brief introduction, SO originates from the fields of physics and chemistry in which patterns seem to emerge in different materials and circumstances at the macroscopic level out of microscopic interactions (Bonabeau, Dorigo, & Theraulaz, 1999, p. 6).

The insight regarding SO and social insects allows concepts of decentralized intelligent system design and problem solving to be transferred to the other domains such as robotics and computer science. Social insects are able to solve complex problems without pre-programming in a robust and flexible manner. Their flexibility allows adaptation to changing environment conditions. Robustness allows the society to keep on functioning regardless of individual insects' failure. This distributed problem solving approach has been labeled "swarm intelligence" (Bonabeau, Dorigo, & Theraulaz, 1999, p. 7).

Despite the simplicity of the local rule sets required, swarm intelligent systems are difficult to design. It is simply difficult to predict what complex emergent behavior will result out of the pre-programmed rule set because it is highly dependent on the local interactions and environment. One approach suggested for swarm intelligence design is to apply the research based understanding of social insects local rule sets and attempt to model tasks performed. This basic model can then be artificially enhanced or varied to adjust to different tasks or algorithms.

The original term of swarm intelligence was used in the context of cellular robotics in which agents self-organized through nearest-neighbors interactions. Bonabeau, Dorigo and Theraulaz extend this definition to "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies." They also stressed that the idea of using simple agents or automata to solve optimization and control problems on graphs and networks was already presented by different researchers as early as 1964.

D. SELF-ORGANIZATION

> Self-organization is a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components. The rules specifying the interactions among the system constituent units are executed on the basis of purely local information, without reference to the global pattern, which is an emergent property of the system rather than a property imposed upon the system by an external ordering influence. (Bonabeau, Dorigo, & Theraulaz, 1999, p. 9)

1. Ingredients

Self-organization has four fundamental ingredients: positive feedback, negative feedback, fluctuation amplification, and multiple interactions. These ingredients are relevant for physical, chemical and biological processes.

a. Positive Feedback

Simple behavioral rules that stimulate structure formation. In social insects these include recruitment (e.g., ants and bees encourage more workers to follow a path or direction for a food source) and reinforcement (e.g., in termites building pillars in their nest through pheromones in the building material). Positive feedback is a result of interactions and can be implemented through direct communication or indirect stimuli / catalyst through the environment (Bonabeau, Dorigo, & Theraulaz, 1999, p. 9).

b. Negative Feedback

Counterbalance for the amplification process and stability are required for the collective process. Different forms of negative feedback include: saturation, exhaustion or competition (Bonabeau, Dorigo, & Theraulaz, 1999, p. 10).

c. Amplification of Fluctuations

Fluctuation amplification includes randomness and errors. Structures will still form despite random processes and it will also allow new solutions or states to be discovered that may improve the overall system (Bonabeau, Dorigo, & Theraulaz, 1999, p. 10).

d. Multiple Interactions

Self-organization processes rely on multiple interactions, not necessarily multiple agents (an agent's action can later on amplify his subsequent actions through indirect interaction). In most cases, though, multiple agents are required to satisfy some minimum density threshold for a structure to emerge (Bonabeau, Dorigo, & Theraulaz, 1999, p. 11).

2. Characteristics

Self-organized phenomena have some basic characteristics which are listed below (Bonabeau, Dorigo, & Theraulaz, 1999, p. 12).

a. Creation of Spatiotemporal Structures in an Initially Homogeneous Medium

Patterns can be seen in chemical reaction products induced by the reaction oscillation. They can be found in calcium walls in competing coral colonies and in sand dunes formed by winds and gravity (Fisher, 2009, p. xi). With social insects such as honeybees, these spatiotemporal structures can be found on the colony combs where brood, pollen, and honey are arranged. A typical pattern is found in three concentric regions, interpreted as due to specific worker rule sets of deposit and removal ratios (Bonabeau, Dorigo, & Theraulaz, 1999, p. 13).

b. Several Stable States

Depending on initial conditions, stable structures are formed through the mechanisms of amplification and fluctuations. Depending on random initial events, the variations in systemic structures will likely cause convergence to one stable state.

c. Bifurcations

The self-organized system can change significantly if there is some (even minor) change in one of the causal parameters. An example for this is a pheromone threshold level in termites that shifts the swarm into a coordinated building phase due to worker density (Bonabeau, Dorigo, & Theraulaz, 1999, p. 14).

3. Interactions Between Agents

Self-organization requires interaction between agents. These interactions can be direct or indirect.

a. Direct

The observable interaction between agents is through direct communication or stimuli. In social insects, this can be through odor, visual contact or physical contact. In physical particles, this could be by direct collisions, electromagnetic forces or chemical bonds.

b. Indirect / Stigmergy

Indirect interactions are less obvious. Indirect interactions happen through the medium (or the environment) which serve as a work state memory (Heylighen, 2012). One agent's action changes something in the environment, which in turn stimulates another agent to perform a certain action. Stigmergy is the best known mechanism that describes such indirect interactions. The phrase Stigmergy (Stigma – sting or mark, ergon – work) was introduced by the French entomologist Pierre-Paul Grassé in 1959 to describe a mechanism of coordination used by termites in nest building (Heylighen, 2012). Grassé showed that control and coordination of building efforts by termites were not worker-dependent but structure dependent. Structure configuration seemed to stimulate the termites' response, which in turn caused a change in structure which further stimulated the termites to respond. The termites' example shows how the Stigmergy mechanism can enable building coordination by self-organization.

Stigmergy is an interesting concept in a robotics perspective because it allows a group of simple, cheap agents with no direct communication to perform complex tasks. Communication between agents can be reduced to a minimum if required and still allow for coordination of tasks. Stigmergy is also a relevant concept for optimization in algorithms due to its incremental changes which allow one solution to be built as a basis for another solution. Lastly, Stigmergy displays a colony's flexibility as all the agents of the colony react collectively and appropriately (without "pre-programming") when

external changes occur in the environment as if the change was induced by the colony itself (Bonabeau, Dorigo, & Theraulaz, 1999, p. 16).

According to (Bonabeau, Dorigo, & Theraulaz, 1999, p. 208), stigmergy can be divided into two sub-categories: quantitative (or continuous) and qualitative (or discrete). Continuous stigemergy depicts mechanisms in which coordination is facilitated by quantitative variations in the intensity of interactions, which is reliant on the combination of stigmergy and self-organization. Discrete stigmergy differs from continuous stigmergy in that agents interact and respond to qualitative or discrete stimuli. In the termite example, the insects building the pillars were reacting to pheromone levels and gradients, which are quantitative. Discrete stigmergy is based on a discrete set of stimuli. An example for this type of mechanism is given in wasps' nest building. Only certain configurations trigger the addition of a new cell. In qualitative stigmergy, there is no positive feedback that intensifies a certain type of stimulus.

E. AUTONOMOUS CONTROL OF A SWARM

1. Definitions for Autonomy

According to the *Oxford English Dictionary* the word "Autonomy" has several definitions, depending on the domain it is used for. The relevant definitions for this thesis are as following:

- Liberty to follow one's will; control over one's own affairs; freedom from external influence, personal independence.
- With reference to a thing: the fact or quality of being unrelated to anything else, self-containedness; independence from external influence or control, self-sufficiency.
- Biology: The condition of an organism, or part of one, of being (to some degree) free from dependence upon or regulation by other organisms or parts; organic independence. (Oxford University Press, 2012)

Another useful taxonomy when dealing with autonomous agents is from the Human Systems Integration (HSI) field. Looking at automation levels in systems involving human-machine interfaces (or interactions) the HSI domain has adopted the following definitions for Levels of Automation (LOA):

1) The computer offers no assistance: Human must take all decisions and actions.

2) The computer offers a complete set of decision/action alternatives, or

3) Narrows the selection down to a few, or

4) Suggests one alternative;

5) Executes that suggestion if the human approves, or

6) Allows the human a restricted time to veto before automatic execution, or

7) Executes automatically, then necessarily informs the human, and

8) Informs the human only if asked, or

9) Informs the human only if it, the computer, decides to.

10) The computer decides everything and acts autonomously, ignoring the human.

(Sheridan, 2011, p. 662)

Another important aspect to note is that while direct (physical) control of the agent can be done autonomously or by a human operator, the same applies to supervisory control. Supervisory control is the idea that *a human supervisor instructs and gets feedback through an intermediary computer which itself closes a direct control loop through an artificial measurement means and a feedback-controlled process* (Sheridan, 2011, p. 663). This means that supervisory control can be done by an Artificial Intelligence (AI) as well.

When discussing centralized versus autonomous control, it is important to be clear about what we mean. In the following research we do not distinguish between a human and AI operator per se but focus on the control mechanism through information flow. That is, we are interested in distinguishing between a global based centralized source of information and decision making to an agent based one. The differences will be further discussed in later sections.

2. Reactive Collective vs. Proactive

It is important to notice that while the general discussion of swarm based tactics includes the case of proactive agents or centralized control mechanism aiming for a certain goal, this is not the case in the "swarm intelligence" perspective. Optimization algorithms (as discussed in the next section) and social-insects-inspired cybernetics are strongly based on the notion of a swarm as a reactive collective. This means that in these domains, by definition, a "swarm" is not centrally controlled and does not have an awareness of a higher goal to be achieved. It [the swarm] simply "reacts." Given this view, if we take an example of UAVs flying in formation and completing a pre-determined tour via assigned waypoints, should they be considered as a swarm? This question is offered for consideration as we discuss swarm definitions further.

F. SWARM INTELLIGENCE FUNDAMENTAL ALGORITHMS AND MODELS

1. Ant Colony Optimization

Ants are required to establish efficient routes to their food sources in order to expend as minimal energy possible when transporting food back to their nest (Fisher, 2009, p. 37). Through an experiment conducted in the University of Brussels, researchers were able to find the method ants use to "optimize" their route. A bridge with two optional routes (long and short) was laid down between the nest and the food source. After an initial random start, it was observed that all the ants had shifted to the shorter path. The ants leave a pheromone trail in their path. The shortest path will exhibit faster return of ants (i.e., more pheromone per time unit) and will therefore reinforce (through positive feedback) additional ants to go through the same path. The pheromone concentration on the shortest path will continue to rise until all ants will have shifted to it.

Inspired by ant logic, researchers have developed an algorithm called "Ant Colony Optimization" (ACO). This algorithm can be used to solve different sets of problems. One of the famous applications is to the Travelling Salesman Problem (TSP) in which the shortest route between *n* cities needs to be determined (Bonabeau, Dorigo, & Theraulaz, 1999, p. 40). This problem tends to become extremely hard to solve for larger *n* numbers. Recent developments of the ACO algorithm which include local search approach have showed performance similar to the best heuristic approaches (Bonabeau, Dorigo, & Theraulaz, 1999, p. 41).

In the ACO algorithm, a "virtual pheromone" is used as reinforcement to facilitate memory of good solutions from which better solutions can be developed. Pheromone "evaporation" (time decay) is used to prevent system convergence into sub-optimal solutions (i.e., *stagnation*). A long decay-constant will result in stagnation while a short delay-constant will not allow for cooperative behavior to emerge (Bonabeau, Dorigo, & Theraulaz, 1999, p. 41).

In the following section a brief description of "Ant System (AS)," the original ACO algorithm initiated by Marco Dorigo for the TSP will be given. The local search augmentation used in "Ant Colony System (ACS)" to improve AS performance, will not be discussed here, but can be found in (Bonabeau, Dorigo, & Theraulaz, 1999, p. 47).

According to (Bonabeau, Dorigo, & Theraulaz, 1999), in TSP we aim to find the minimal length tour connecting n cities. Each city must be visited exactly once. In AS, ants move on the problem "graph" until a tour is completed. In each iteration, each one of the *m* ants conducts an n steps tour. The algorithm is limited to a defined t<T_{max} total number of iterations. The transition rule for the probability of a single ant moving from City *i* to City *j* in one iteration is:

$$P_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}(t)\right]^{\beta}}{\sum_{l \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} \cdot \left[\eta_{il}(t)\right]^{\beta}} \tag{1}$$

In Equation (1), *i* is the current city the ant *k* is in, and *j* is the next city being "considered" for transition by that ant. J_i^k is the set of cities not yet visited for ant *k* located in city *i*. $\eta_{ij} = 1/d_{ij}$ is the inverse of the distance between cities *i, j* and is called *visibility*. "Visibility represents the heuristic desirability of choosing city *j* when in city *i*" (Bonabeau, Dorigo, & Theraulaz, 1999, p. 42). Visibility is local information that is kept constant throughout the simulation. τ_{ij} is the virtual pheromone trail level on the edge connecting cities *i* and *j*. Pheromone levels update online and display the learning of desired transition from *i* to *j*. It is important to note that pheromone level is a global information source as opposed to visibility. The transition rule in (1) applies only if $j \in J_i^k$ (i.e., city *j* has not been visited yet) otherwise the probability is zero. α and β are weighting parameters for the pheromone level and visibility.

After finishing a tour, each ant *k* leaves a portion of pheromone $\Delta\tau_{ij}^{k}(t)$ on each edge *(i,j)* that it has been to in the *t* iteration. The portion of pheromone depends on the how short the tour was and is given by (Bonabeau, Dorigo, & Theraulaz, 1999, p. 43):

$$\Delta\tau_{ij}^{k}(t)=\begin{cases} Q/L^{k}(t) & \text{if } (i,j)\in T^{k}(t); \\ 0 & \text{if } (i,j)\notin T^{k}(t) \end{cases} \tag{2}$$

In (2), $T^{k}(t)$ is the tour performed by ant *k* in iteration *t*, $L^{k}(t)$ is the tour length, and Q is an adjustable parameter.

To avoid stagnation and to allow exploration of a variety of solutions, pheromone decay ρ ($0<\rho<1$) is used to update pheromone levels, as following:

$$\tau_{ij}(t)\leftarrow(1-\rho)\cdot\tau_{ij}(t)+\Delta\tau_{ij}(t) \tag{3}$$

In (3), $\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t)$ and *m* is the total number of ants. The number of ants selected has similar effect as the decay constant on solution convergence and cooperative potential between the ants. The AS algorithm was further improved by introduction of several "elitist" ants which add pheromones only to the best tour found from the beginning of the simulation. The full High-level description of the AS algorithm to solve the TSP can be found in (Bonabeau, Dorigo, & Theraulaz, 1999, p. 45).

2. Particle Swarm Optimization

The particle swarm optimization algorithm (PSO) was first introduced by Eberhart and Kennedy in 1997. Their goal was to find a "form of computerized swarm-intelligence with the broadest possible problem-solving ability" (Fisher, 2009, p. 43).

The particle swarm concept is related to the Adaptive Culture Model which is based on Axelrod's Culture Model from 1997 (Kennedy & Eberhart, 2001, p. 263). Axelrod proposed a computational model for the dissemination of culture through interactions between similar individuals. Eberhart and Kennedy considered Axelrod's model to contain the fundamental principles for their swarm algorithms. The Adaptive Culture model showed that cognitions, attitudes and other psychological phenomena are optimized through interaction. This optimization shows that the simplest interaction between agents allows a computer-based population in a multi-dimensional problem space to "find" solutions and patterns to different problems. These individuals do not have any self-drive to solve the global problem, they simply follow the simple local rule set.

The particle swarm socio-cognitive theory is based on three basic behaviors of individuals (Kennedy & Eberhart, 2001, p. 288):

- Evaluate
- Compare
- Imitate

Evaluation depicts the tendency to rate stimuli as positive or negative. For the agent to learn he must be able to evaluate his environment. Comparison is the basic way for agents to self-evaluate themselves compared to their neighbors. Imitation is the way the agents learn and change. If an agent's neighbors are evaluated to be superior, the agent will be more prone to advance in their direction. The combination of all three basic principles allows the computerized population to solve complex problems and adapt to changing environment. The "thinking" process becomes a social process and not inside the individual agent.

The PSO algorithm solves an optimization problem in multiple dimensions. Each particle in space represents an agent's "state of mind," which has properties in several dimensions (in the sociological point of view these could be attitude, emotion and other properties). Different regions in the problem space have different values for the objective function.

A short description of the algorithm: $\vec{x}_i$, $\vec{v}_i$ are the position and velocity vectors for particle *i*, respectively. The particle must be moved to search the problem space while looking for an optimum. This is done by changing the velocity, according to the influence of your neighbors (equivalent to social connections in society). It is important to notice that neighbors are pre-defined by their index *i* and not by their proximity in the problem space. This is logically consistent with the fact that people are affected by their people whom they have a social connection with and not people that have the same views as they do (and they may have never met before). The particle's next position is given in Equation (4). The direction of movement is influenced by the particles previous position, velocity, best self-recorded position and best neighbor-recorded position.

$$\vec{x}_i(t) = f(\vec{x}_i(t-1), \vec{v}_i(t-1), \vec{p}_i, \vec{p}_g) \tag{4}$$

Velocity is a function of the difference between the particle's recorded-best position and current position and the difference between the neighbor-recorded best position and the particle's current position. The set of equations (5) define this relationship:

$$\begin{cases} \vec{v}_i(t) = \vec{v}_i(t-1) + \varphi_1(\vec{p}_i - \vec{x}_i(t-1)) + \varphi_2(\vec{p}_g - \vec{x}_i(t-1)) \\ \vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \end{cases} \tag{5}$$

The φ weights variables are random numbers defined by an upper limit. This produces a cycle around the weighted average of the self and neighbor best. Due to the random numbers, this point will shift on each iteration of the algorithm.

To prevent velocity explosion, a limit of V_{max} is defined for any dimension. The swarm will continue to oscillate in bounds without converging to a final point. Nonetheless, it will be successful in finding improved solutions closer to the optimum.

To control the search, different methods such as inertia weights or constriction coefficients are used.

The Pseudo-code for particle swarm optimization in continuous numbers from (Kennedy & Eberhart, 2001, p. 313) is presented in Figure 1.

Loop
 For i=1 to number of particles
  if $G(\vec{x}_i) > G(\vec{p}_i)$ then do //G() evaluates fitness
   For d=1 to number of dimensions
    $p_{id} = x_{id}$ //p_{id} is best so far
   next d
  End do

  g=i //arbitrary
  For j=1 to indexes of neighbors
   if $G(\vec{p}_j) > G(\vec{p}_g)$ then g=j //g is the index of the best performer in the neighborhood

  Next j
  For d=1 to number of dimensions

$$\begin{cases} v_{id}(t) = v_{id}(t-1) + \varphi_1(p_{id} - x_{id}(t-1)) + \varphi_2(p_{gd} - x_{id}(t-1)) \\ v_{id} \in \left(-V_{\max}, +V_{\max}\right) \\ x_{id}(t) = x_{id}(t-1) + v_{id}(t) \end{cases}$$

  Next d
 Next i
Until criterion

Figure 1 Pseudo-code for Particle Swarm Optimization Algorithm after (Kennedy & Eberhart, 2001)

PSO algorithms have been found to be extremely efficient in different optimizing problems, especially those with abrupt changes in the problem "topography" (Fisher, 2009, p. 44). PSO is currently used in investment decision-making, MRI and satellite scans analysis and movement detection in image processing.

3. Cellular Automata (MANA Agent Based Model)

Map Aware Non uniform Automata (MANA) belongs to a general class of agent-based models (ABMs) (McIntosh, Galligan, Mark, & Michael, 2007). ABMs contain agents that are controlled by decision-making algorithms. This means their behavior is not pre-determined, but they are rather given a rule set and logic (as weights) for those rules as a basis for their decision-making. MANA also belongs to an additional subset of models called Cellular Automata (CA). CA has been used to model physical and biological phenomenon (e.g., magnetic spin alignment). MANA is also referred to as a Complex Adaptive System (CAS). According to (McIntosh, Galligan, Mark, & Michael, 2007) the characteristic properties of CAS are:

- The global behavior of the system emerges as a result of multiple interactions.
- A process of feedback that is not reductionist, top-down models.
- They cannot be analyzed by decomposition to smaller independent parts.
- Agents interact in non-linear ways with each other and the environment.

MANA attempts to model important combat factors such as an evolving battle plan, situational awareness information and data from sensors.

Each agent in MANA has user defined personality weightings associated with information inputs received via communications or the agent's sensors. With these weightings, a penalty calculation can be calculated for every agent in each time step to decide upon its next movement. The equivalent force vector exerted on an agent is calculated by the multiplication of each input vector (enemy/waypoint) by its corresponding weight (McIntosh G. C., 2009). The force is then used to calculate the agent's acceleration (given a default mass). The agent's new location is then given by the simple kinematic equations:

$$\begin{cases} \Delta\vec{r} = \vec{v}\Delta t + \dfrac{a(\Delta t)^2}{2} \\ \Delta\vec{v} = a\Delta t \end{cases} \tag{6}$$

G. SWARM INTELLIGENCE IN CYBERNETICS

The swarm-inspired robotics field has seen considerable attention and efforts in the past years. Future civilian applications include aerospace and environmental maintenance, inspections and communication relays. Medical applications inside the human body are envisioned through harnessing future nanotechnology and bio-mechanical capabilities (Bogue, 2008). The next sections highlight key points in swarm-robotics.

1. Advantages of Swarm-Based Robotics

There are several reasons why swarm-based robotics is an attractive concept. The major reasons are listed below (Bonabeau, Dorigo, & Theraulaz, 1999, p. 20).

- Some tasks are too complex for a single robot to execute.
- Speed to accomplish task can be significantly improved.
- In many cases, it is much cheaper to build multiple simple robots (simple sensors, motors and processing) than one complicated unit.
- Flexibility (no reprogramming). Flexible adaptation to different situations is inherent in swarm logic.
- Reliability (or robustness) is also inherent in swarm robotics because a single robots failure does not make the mission a failure. There are no single-fail points.
- Swarm logic supports emergent solutions not originally thought of by the designers.
- Reduction of inter-robots communications through the concept of stigmergy.
- Swarms do not require central control which is a bottleneck for communication and a possible single point of failure.

2. Disadvantages of Swarm-Based Robotics

Due to the local rule set reactive logic implemented in swarm robotics, it is important to note the major (known) pitfalls.

- Stagnation – due to the lack of global perspective a swarm of robots may find itself in a dead-end with no knowledge how to advance. In swarm based algorithms this can be seen in the methods developed in the attempt to prevent possible convergence to a suboptimal solution.
- It is difficult to pre-program and predict how a simple rule set with environmental interactions will emerge with the desired macro user-task.

The point about stagnation is important for this thesis argument that there is a benefit in "understanding" an opponent swarm's underlying mechanisms to find a possible opportunity for exploitation. In addition, the second point is also crucial for the sake of this study. While a set of local rules may have several outcomes (given slightly different conditions), the opposite argument has a high probability of being true as well. That is, a single emergent behavior may originate from several different local rule sets or mechanisms. This basic, logical limitation, clarifies the boundaries of and uncertainty about the absolute possible knowledge that can be obtained from swarm "observations."

3. Swarm-Inspired Implemented Robotics Mechanisms

Current working swarm based reactive-collective robotics are still maturing. This field is relatively new and requires a shift in fundamental paradigms related to classic AI. The following sections discuss some working examples.

a. Swarm Based Distributed Control

One of first implementations of distributed control was distributed clustering by a group of robots (Bonabeau, Dorigo, & Theraulaz, 1999, p. 173). These robots used grippers with mechanical sensors to evaluate physical resistance. Higher physical resistance correlated to high density of pucks that required clustering. By simple avoidance rules and a reverse action rule (when the perceived pucks resistance exceeds a threshold) the spatial clustering process as discovered in termites could be reproduced.

Current efforts in distributed control can be found in the EU-funded "SYMBARION" (Symbiotic Evolutionary Robot Organisms) project and "REPLICATOR" (Robotic Evolutionary Self-Programming and Self-Assembling Organisms). These ambitious projects aim at developing organism-like cooperation between autonomous self-sustaining and processing micro-robots. These robots will have the ability to assemble to larger formations and perform tasks according to external environmental conditions without pre-programming (Bogue, 2008, pp. 490–491).

b. *Coordination*

A crucial step in swarm based-robotics is the coordination of agents' movement and actions by simple rule sets to achieve a goal or avoid collisions. One of the earliest attempts to model swarm movement coordination was implemented in a computer-simulation called *Boids* by Craig Reynolds in 1986. The Boid simulation was used for animation purposes and is still considered the basis for today's elaborate movie animations depicting crowds of people or animals. The fascinating concept behind the simulation is the simplicity of the rule sets each agent follows to produce the global life-like flock (or school) behavior. The individual Boid follows three rules (Fisher, 2009, pp. 26–27):

- Avoid bumping into other individuals
- Move in the average direction that your neighbors are heading.
- Move toward the average position of those closest to you.

These rules are also described as:

- Avoidance (separation)
- Alignment
- Attraction (cohesion)

These three rules seem to apply to human crowds, over a certain density threshold, as well (Fisher, 2009).

An example of coordinated robots' actions to perform a task was also found in the benchmark study task of cooperative "box" transport (Bonabeau, Dorigo, & Theraulaz, 1999, pp. 260–265). In this problem, a group of robots worked cooperatively to "push" an object in a desired direction. This effort was inspired by the cooperative transport of large prey by ants to their nest. The uniqueness of this transport coordination was it is done with no "global" planning or direct communication. The box itself was the medium of indirect communication. This coordination type was a form of quantitative (or continuous) stigmergy. This problem is promising for a swarm of robots to implement as scaling the number of robots in the problem does not require any change in single robot's logic. A fully stigmergic implementation of box transport by 5 robots was

achieved by Kube and Zhang (Kube & Zhang, 1997). In their experiments, an illuminated box attracted the robots (using photocells) which in turn pushed the box to the edge of an arena. While in general the transport speed is reduced with increasing numbers of agents involved, the efficiency (defined as [box weight x velocity] / # of agents)) increases. Lastly, it is important to mention that cooperative transport is subject to stagnation due to agents pushing in opposite directions, heavy loads, or an obstacle on the substrate. To avoid stagnation, recovery methods were implemented by the robots (inspired from ants). These recovery methods initially included realigning the force direction. If realigning does not work, repositioning of agents around the box was used. Realignment and repositioning were more frequent at the beginning of the process in which the box dids not move much. After a certain time period a "phase transition" occurs, direction was set and the box moves fairly smoothly to its goal (Bonabeau, Dorigo, & Theraulaz, 1999, p. 261).

H. PHYSICS-BASED SWARMS AND ENTROPY

1. Physicomimetics

A different approach to swarms is physics-based. This domain has been branded *physicomimetics* in contrast with *biomimetics* domains such as social insects inspired swarm intelligence. This field focuses on swarms of matter particles as metaphors for robots, agents or points on an *n*-dimensional optimization space (Spears, 2011, p. 3). These particles may have properties such as location, speed and mass and are subject to interactions with other particles through various potential / force fields. These swarms may behave as solids, liquids or gas.

One of the first physicomimetics models was based on potential fields. A group of robots navigated through a field of obstacles to get to a destination, using global virtual environmental forces. The environment, rather than the agents, exerts forces. Obstacles exert repulsive forces while goals exert attractive forces (Spears, 2011, p. 7). Further research turned away from global potential fields, due to the vulnerability of this approach, and emphasized fields exerted by other agents.

Biomimetics flocking approaches that utilize velocity matching of an agent with its neighbors are also physics-based. Biomimetics excel in describing flocks, social insects, human crowds and optimization algorithms. In comparison, physics-based swarm approaches are useful in physical-engines based graphical simulations, in area coverage problems and self-organization to achieve minimal energy loss. This last notion is important when considering the implementation of robot-swarms that will always have limited resources constraints.

(Spears, 2011, p. 10) Lists the motivation of using physics-based models for swarms:

- Physical principles provide for deriving macroscopic behavior from microscopic interactions
- Physics is a reductionist approach, allowing us to express the macroscopic behavior elegantly and simply.
- Physics is the most predictive science.
- Physical systems are naturally robust and fault-tolerant.
- Low-level physical systems can also self-organize and self-repair.
- The physical world is often based on low energy consumption and usage.

The last point relates to the minimum energy or least action principle in nature. This point also leads us to the next section dealing with entropy.

2. Entropy

The concept of entropy is used in thermodynamics, statistical mechanics and information theory. The first law of thermodynamics states that for a compressible gas $dU = -pdV + Tds$. This means that entropy is dependent on the gas internal energy and other parameters such as volume. Entropy describes a system’s state and is a measure for the energy not available for work in the system. The second law of thermodynamics discovered by Clausius states that the entropy of an isolated system will never decrease.

The statistical mechanics definition of entropy was given by Boltzmann and describes the number of micro-states the system can be in given a certain macro-state. The mathematical formulation is given in Equation (7):

$$S = -k_B \sum_i p_i \log p_i \tag{7}$$

In Equation (7), k_B is the Boltzmann constant and p_i is the probability that the system is in the micro-state i. As the number of possible states increases, the entropy increases as well. From this definition we can understand why entropy is used as a measure of disorder or the uncertainty we have regarding the system's state. As the systems entropy increases, its probability distribution is allocated to more possible micro-states that the system may occupy.

Spatial entropy is used in image processing and to track the dynamics of clustering. Spatial entropy can be used to measure how well items or swarm agents are clustered in different spatial scales (Bonabeau, Dorigo, & Theraulaz, 1999, p. 154). For a certain spatial scale *s*, the related spatial entropy for that scale is given in Equation (8):

$$E_s = \sum_{i \in \{s-patches\}} p_i \log p_i \tag{8}$$

In Equation (8), p_i is the fraction of all objects on the lattice that are found in *s*-patch *i*. Spatial entropy decreases as clustering proceeds (as the system is "gaining order") and thus can be used to identify the timing of different clustering strategies in different scales.

3. Fractal Dimensions

A fractal dimension is an index that describes the changing level of detail with the change in scale. The term fractal dimension was labeled by Benoît Mandelbrot in 1975. In his paper from 1967, "How Long Is the Coast of Britain?" he discusses the paradox of the dependency of the answer on the length of the measuring stick (Mandelbrot, 1983). That is, the shorter the length of the stick, the longer the total length will become. A fractal dimension does not necessarily have an integer value.

Mathematically, one can use the scaling rule in Equation (9) to measure the fractal dimension.

$$N \propto \varepsilon^{-D} \Rightarrow -D = \frac{\log N}{\log \varepsilon} \qquad (9)$$

In Equation (9), N is the number of new sticks (or boxes), ε is the scaling factor and D is the dimension. For one dimensional lines scaling 1/2 will require twice the sticks, therefore *D*=1. For a cube scaling by 1/2 will require 8 cubes and therefore *D*=3. For a fractal pattern such as the Koch curve scaling of 1/3 will require 4 times the stick length and therefore the fractal dimension will be 1.2619. A fractal dimension 1 < *D*f < 2 implies that the pattern has more detail and space filling properties than a conventional 1D line. A fractal dimension closer to 2 indicates that the line moves and fills the space almost as a surface.

In real-life observations, scaling units and ratios are unknown in advance. The use of slope limits on log-log plots of scale to size are used to estimate the fractal dimension. Several different definitions exist, but in this thesis, the one used is the "Box Counting" / "Capacity" dimension definition (Weisstein, 2012) as shown in Equation (10). This definition is suitable for implementation on an image matrix in the MATLAB environment.

$$D = -\lim_{\varepsilon \to 0} \frac{\log N}{\log \varepsilon} \qquad (10)$$

In this thesis the "boxcount" package for MATLAB (Moisy, 2008) is used to develop time dependent fractal dimension plots.

I. SWARM INTELLIGENCE IN SOCIOLOGY

Swarm intelligence has applications and insights for human behavior. One may ask how this statement is true when we have only discussed swarms in the context of groups of "simple" agents. The answer lies in the fact that while each human individual is indeed a complex agent, in certain scenarios, the overall behavior of a group of people has direct analogies to swarm concepts.

1. Crowd Control

When a large group of people are constrained to a limited space a crowd is formed. Crowd dynamics studies distinguish between two forces acting on an individual in the crowd (Fisher, 2009, p. 50). One force is "physical" and describes the involuntary "pushing" force we feel from the crowd or physical obstacles. The second force is "social" and describes our will to move to different location (stay close to family, avoid bumping into other people).

When crowd density is low, Reynolds three rules for "Boids" apply (avoidance, alignment, attraction). This phenomena can be seen in emergent formations of streams (or lines) of people walking in opposite directions in a crowded street. No centralized control is used to organize them. The formations emerge from the basic rules above an average density of one pedestrian every two square feet. These "lanes" reduce friction, or declaration of the people moving through the confined space (Fisher, 2009, p. 54).

When crowd densities become high, movement patterns change. Confined spaces become jammed and in the worst cases panic can set in resulting in injuries and even fatalities. When density rises over one and a half square feet per person an individual is moved by physical forces with no control over direction of movement. Propagation of pressure waves and force chains are formed in the crowd and easily knock people down. The most tragic crowd disaster occurred in Mina, in Saudi Arabia when 346 pilgrims were killed during the Muslim hajj (Fisher, 2009, p. 63). Studies from security cameras' footage of this event have helped implement preventive measures against crowd densities build up.

2. Invisible Leaders

Observations of bee swarms have revealed that several individual bees inside the greater swarm fly faster and in straighter lines than the rest of the swarms. These bees' velocities are aimed at the swarm target destination. Computer simulations have revealed that without designating these bees as leaders the mere fact that a few individuals in the swarm know the correct direction is enough to lead the entire swarm. The rest of the bees do not even know they are following others (Fisher, 2009, p. 30).

Could similar results apply to human beings? An experiment with students proved that it could. A group of 200 students was told to walk around the room and keep within close distance to at least one other person. They were not given any specific goal. A small group of 10 students were secretly given the task to go to a specific location without leaving the group. When the experiment was over most of the students had ended up near the same location. Similar examples can be found in riot controls when police forces remove a portion of trouble-makers to control the crowd. It appears that the individual's ability to influence a group has subtle dependencies on positive and negative feedback loops and cascading chain reactions (Fisher, 2009, p. 35).

3. Group Decision Making

Group decision making is an important aspect of social sciences and life in general. How do groups make decision? Do all members need to agree unanimously? Should one expert be given full authority to make decisions for the rest of the group? These questions are relevant to our understanding of how humans decide as a collective.

In this section three major concepts are presented: Collective intelligence, majority opinion and group think.

Collective intelligence is a term that refers to the notion that a group's average estimation of a systems current state (out of many possible ones) <u>always</u> outperforms most of its individual members (Fisher, 2009, p. 69). As the group size increases so does the estimation accuracy. This phenomenon is explained through the correction of errors by taking the statistical average. Many different experiments have reproduced this result over the years, most of which involve a group guessing the amount or weight of certain objects. It is important to note the following (Fisher, 2009, p. 74):

- Group intelligence will perform only when individuals' estimates are independent of each other.
- The group will outperform <u>most</u> of its members, not all of them.
- Group intelligence relies on cognitive diversity. This includes diversity in knowledge, perspectives, interpretations, heuristics and predictive models.

Majority opinion describes the fact that if most of the members of a group are moderately well informed (over 50% probability of being right) than the majority opinion is almost always bound to be right. For example, if an individual has a sixty percent probability of being right than the group's answer will have a 99% chance of being correct. This mathematical fact was proved in Condorcet's jury theorem which had set out to prove why a rational citizen should accept the authority of the state in the democratic process. The jury theorem relies on independent opinions as well (Fisher, 2009, p. 77).

Group think is a term coined by Yale psychologist Irving Janis and describes a situation in which social pressures within the group push its members into a pattern of thoughts that is characterized by self-deception, forced manufacture of consent, and conformity to group values and ethics (Fisher, 2009, p. 93). This phenomenon has led to countless cases of bad decision-making throughout history. It is obvious that the consensus force in work here counteracts the very fundaments of group intelligence, diversity.

4. Swarm Organizations

There are several interesting cases of organizations implementing swarm intelligence and group intelligence in their organizational structure and operations to produce better results. In the following section some examples are given:

a. "digg" Website

The "digg" website allows users to upload news items they have found interesting on the web. Other users rate the items they have read. If an item does not receive sufficient users ratings it will quickly drop in the list ranking. This form of rating is analogous to pheromone levels in ant colony optimization. The "pheromone" decays over time if users do not continue to deposit pheromone / ratings. This method assures only interesting items remain on the list, and also allows for positive feedback. More user ratings will expose the item to more users which will in turn increase the amount of ratings (Fisher, 2009, p. 42).

b. Wikipedia

Wikipedia is an example of a non-profit organization that harnesses the power of its distributed contributors. There is no centralized editing or writing. Each contributor feels as a stakeholder in the overall endeavor. Articles are improved by several contributors. An article is reviewed through constant feedback and corrections. An important aspect in this operation is that there are no limitations to who can edit. Editors receive additional authority or prioritization based on their past contributions record in a positive feedback loop.

c. Amazon

Amazon.com allows customers to post product reviews for other customers to use. This is also analogous in a way to pheromone advertising good product solutions. Amazon also utilizes swarm concepts by offering a platform on which businesses and customers can perform their interactions with relative simplicity by supporting functions given by Amazon (Fisher, 2009, p. 104).

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VI. AN INTEGRATIVE MODEL FOR THE SWARM

A. THE TACTICAL INPORTANCE FOR AN OPPONENT SWARM MODEL.

Before developing a theoretical approach for a swarm model, one must ask what the need for such a model is. Why would there be interest in such a model? What are the possible benefits?

1. The Swarm Threat

Tactical swarm threats have raised concerns regarding the gap in current military weapon systems counter capabilities. In (Hughes, 2009) anti-swarm capabilities are discussed as critical for the "New Navy Fighting Machine." A commonly discussed swarm threat is the U.S. Navy defined Fast Inshore Attack Craft (FIAC) threat. The FIACs display a threat to Navy ships or high value units (HVU) from a fast moving surface craft. The FIAC threat is enhanced in its manifestation as a swarm of fast attack crafts carrying surface to surface missiles (Hughes, 2009). Other possible threats to Navy assets are expendable UAV swarms that explode upon impact with their target (Kospoth, 2009).

2. Current Proposed Solutions

The examples given above are merely an indication of potential future swarm-threats to conventional military platforms and tactics. To focus the argument for the necessity of a swarm model, the current protection of a High Value Unit (HVU) against an incoming swarm of unmanned surface Vehicles (USVs) or UAVs is considered. Solutions proposed for such anti-swarm protection include: CIWS gun adaptation (Ewing, 2011), loitering interceptors as the NLOS-LS program (New Wars, 2010) and focused energy weapons as the Mk 38 Mod 2 tactical laser system (Defense Update, 2011). One FIAC dedicated solution demonstrated by Lockheed Martin involves use of dedicated onboard and external radar, optical sensors and Hellfire missiles to extend the defensive perimeter of most Naval vessels out to five miles (Defense Update, 2007). While all these systems aim to solve the incoming swarm threat, none of them assure zero

leakers penetration, especially against high volume, synchronized attacks. It would seem that enhancing the properties of our current capabilities with similar tactics is not sufficient to achieve a holistic solution.

3. Why are Current Solutions Insufficient?

All of the suggested solutions above are based on enhanced properties such as: range, P_k, or fire rate. The reason this approach cannot provide a complete solution is inherent in the swarm properties, as discussed in the literature review:

a. Scaling

The number of agents in the swarm can be relatively easily increased given the need, as scaling and production is made simple through distributed control mechanisms and possibly simple and cheap swarm agent units. Enhancing existing counter measures properties such as fire rate can be easily met by scaling up the swarm size. In this "race" of fire power versus numerical superiority, Lanchester's equations' most famous insight reflects what seems obvious: numbers win.

b. Robustness

As a single agent is disabled the swarm continues to function with little effect on the swarm's collective performance. The lack of a single point of failure is the key to the swarm's robustness. In the case of the FIAC threat, a single "leaker" may be enough to disable the HVU. The combination of a "single leaker" threat with the swarm robustness means that a defense system must ensure 100% of swarm agents are intercepted. Any enhancement of fire power / range will not ensure this requirement is met, as the system will eventually reach saturation by a swarm and performance of the defenders will degrade with increasing threats.

c. Flexibility

Swarm flexibility is achieved through adaptation to changing environment. As the example given by stigmergy, the agents interact through the environment as a medium and therefore display flexible behaviors with respect to changes in it. As an example, a swarm of attacking FIACs can be easily configured to advance in a route with the least defenders presence. As the defender's units change positions, the swarm will adapt collectively and change its course to gaps perceived in the

defender's formation. Swarm agents can also be configured to avoid routes in which other swarm agents have been disabled in and to pursue successful routes through processes resembling pheromone usage.

4. Potential Swarm Weaknesses

A system that aims for a complete counter swarm capability must not try to counter it head on, unless time of engagement, number of defenders, and context favor the defense. Instead, the system must attempt to utilize the swarm's potential weaknesses:

a. Situational Awareness Related Stagnation

A swarm that is based on local information from its agents (i.e., each agent actions are the result of stimuli from its own sensors) is subject to the risk of convergence to sub-optimal solution / action due to lack of global knowledge (Bonabeau, Dorigo, & Theraulaz, 1999).

b. Centralized Control

A swarm that is controlled by an external / internal centralized function has a possible single point of failure. Failures in the control function or the link to the swarm are single point failures and thus not robust (Bonabeau, Dorigo, & Theraulaz, 1999).

c. Communications

A communications-reliant swarm may have a "bottle-neck" that creates delay in the centralized control scheme. This bottle-neck is due to the difficulty to scale bandwidth with the swarm size while complying with link quality constraints (Bonabeau, Dorigo, & Theraulaz, 1999). In distributed control, communication-reliance may create range dependency (due to SNR limitations) between agents and delays in the collective reaction time. These challenges are related to the difficulties in implementing high bandwidth Mobile Ad-hoc Networks that are crucial for future network centric unmanned platforms. Exploitation of communications weaknesses can come in many forms (e.g., Interfere, Intercept, and Masquerade) which could have different potential effects on the swarm. A simple effect of communication interference could be de-synchronization of the swarm movement patterns due to induced transmission delays. These could result in

unsynchronized swarm attacks. Depending on the implemented swarm tactic, this would shift the force ratio in favor of the defender or render the attack completely ineffective. Masquerading methods could enable injection of harmful information into the swarm network and could have a viral effect, spreading quickly throughout the entire swarm agent population.

d. Transition Phase

Tactical swarms may implement hybrid control mechanisms in which a transition between full operator control and autonomous control is possible. Exploitation of the transition phase between these control mechanisms may lead to a meta-stable condition which will render the swarm ineffective. This exploitation concept is out of scope for this thesis, although initial discussions suggest this concept may have potential for future research.

5. Categorization of a Swarm in Order to Exploit Relevant Weaknesses

In order to utilize the weaknesses mentioned above, the defender must first understand the underlying mechanism of the incoming opponent swarm, as each weakness is relevant for different swarm mechanisms. But without preliminary knowledge of the inner-workings of a swarm agent or access to swarm communication links (if such exists), how can one tell what is the underlying mechanism that operates the swarm?

The following research suggests the possibility to gain significant knowledge of the swarm's underlying mechanism, solely through observations of the swarm agents' movement patterns.

By incorporating a sub-system dedicated to such observations into the defender's counter measures defense-system, a classification into control mechanism categories would be possible. Potential benefits to such an approach include:

- Enabling faster, more appropriate and possibly game-changing responses to a swarm attack.
- Enabling cost-effective swarm counter-measures to be utilized.
- Preliminary understanding of the aim of the swarm.

- Appreciation of the type of command and control operative with the swarm.

B. SYSTEM VIEWS OF A SWARM

As part of the process of critical thinking and the systems engineering process, different system views of a swarm were considered. The following list of views was proposed by Prof. Langford as seeds to spring thought regarding a generalized integrative model for the swarm that would incorporate as many system views possible. System views also operate as "filters" to ease understanding of a certain aspect of a broader problem space. A swarm could be viewed as:

- Resources – as the capacity of agents and capabilities provided by the swarm.
- Dynamics – as the change in spatial patterns.
- Transaction costs (losses) – in the form of material and energy loss.
- Interaction – as a set of EMMI exchanges.
- Complexity – in the form of emergent behaviors.
- Management – centralized or distributed.
- Organizational learning – in the swarms' adaption to different scenarios.
- A Process – in the form of a set of activities to achieve an intended output.
- A Function – depending on the objective of the given swarm.

The following systems views were the views most dominant in this research through the use of several supporting research theories and tools as shown in Table 3:

Research theory / Tool	Key systems views
Statistical mechanics	Dynamics
Taguchi loss functions	Transaction costs, Performance and Quality
Integration theory	Interactions and Processes
Fractal dimensions	Complexity
Functional decomposition	Functions

Table 3. Mapping of supporting research theories / tools to key system views

The use of these research theories and tools will be presented in the following chapters of the "integrative model for the swarm", and the "interpretation of a swarm from an agent based model".

C. STAKEHOLDERS PERSPECTIVES OF A SWARM'S BEHAVIOR

Similarly to the systems views, different stakeholders' perspectives were suggested by Professor Langford as lenses in order to focus the research effort in relevant domains. Thus, stakeholders could view a swarm's behavior from the following viewpoints:

- As a spatial experience – through the spatial structures created by the swarm collective.
- As mathematics – through the underlying algorithms implemented in and geometry presented by the swarm.
- As spatial location(s) – through the physical coordinates occupied by swarm agents.
- As architecture – through the implementation of different C2 mechanisms.
- As coordination - through the implementation of different C2 mechanisms.
- As threat – through offensive maneuvers.
- As vulnerability – through possible stagnation or communications weak points.
- As energy- through the potential and kinetic energy within the swarm.
- As data – through the potential information gain from location, speed, and communicational properties displayed by the swarm agents.

These perspectives of swarm behavior appear throughout this research starting from the literature review and continuing in the following analysis.

D. FUNCTIONAL DECOMPOSITION

According to (Blanchard & Fabrycky, 2011):

> An essential activity in early conceptual and preliminary design is the development of the functional description of the system to serve as a basis for identification of the resources necessary for the system to accomplish its mission. A function refers to a specific or discrete action (or series of actions) that is necessary to achieve a given objective…The functional analysis is an iterative process of translating system requirements into detailed design criteria…it includes breaking requirements at the system level down to the sub-system…

An additional amplification is offered by (Langford, SE3100: Fundamentals of Systems Engineering, 2012).

> Functional decomposition is a fundamental step in functional analysis… [it] allows us to deal with the complexity of the system and our inability to comprehend all aspects of such systems through a formal process of breaking apart (segmenting) the system into more manageable units at the same level of abstraction, and then further segmentation at the next level of increased detail (decomposition)… Problems with poor functional decompositions include: Hindering the ability to integrate functions and map functions to physical domain, [the] creation of unnecessarily complex, numerous interfaces, extensive rework in later stages as detailed problems arise (expensive/time consuming). Problems could arise from: [o]verlap and underlap of functions, abstractions at improper levels, inadequate coupling, cohesion, or connectivity. Coupling measures the interdependence of two functions. Loose coupling inhibits changes in one function affecting the other. Cohesion measures the strength of association of functions. Highly cohesive functions perform one well-defined objective.

The method of functional decomposition outlined above in the passage from Blanchard and Fabryky was used to breakdown the perceived complexity of the swarm concept into manageable segments. A specific swarm type (e.g., ants) is a system that may be easily decomposed to functional elements by relation to known specified actions. As was suggested by Langford's discussion, however, decomposition can be difficult. This proved to be the case for this thesis research: decomposing the abstract, general concept of a swarm proved to be more challenging and admittedly the proposed decomposition is probably still incomplete. Nevertheless, while the final product may not be flawless, there is an inherent benefit to the process itself.

The decomposition process, often referred to as iterative as it requires many different instantiations, was guided by two major verification tests: that the functions were restricted to a level of abstraction that had to fit all swarm domains (as presented in the literature review) and where there was compliance to the coupling and cohesion decomposition requirements.

A graphical representation of the functional decomposition for the swarm and the swarm agent is shown in Figures 2 and 3, respectively:

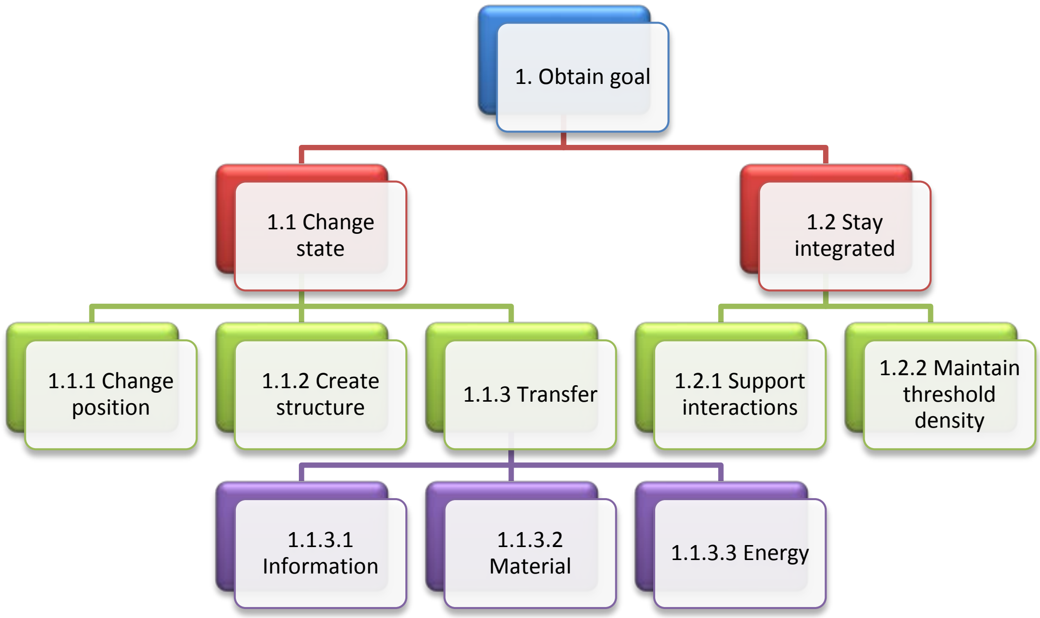

Figure 2 Functional decomposition of the swarm

The functional decomposition as shown in Figure 2 begins with the highest level function of the swarm which is to obtain some goal / objective. In social insects, it may be the survival of the colony and reproduction. In swarm algorithms, it may be to find an optimum solution in a given problem space. The higher objective is then decomposed to its sub-components: "change state" and "remain integrated." To obtain its goal, the swarm must change its state in order to adapt, perform actions and find better swarm-states with respect to the environment. In order to achieve its goal, the swarm must remain integrated (i.e., agents must interact and act according to those interactions). If the swarm does not remain integrated, it is simply a set of objects in space. "Change state" is further decomposed to its elements: "change position (physical movement)," "create structure (a spatiotemporal self-organization)" and "transfer of EMMI" to enable the "state change." In order to stay integrated, the swarm must: "support interactions" (that is enable its agents to interact with each other) and "maintain a threshold density"

(beneath a certain agents' spatial density, interactions will not create an integrative collective, just sporadic interactions with no feedback loops)."

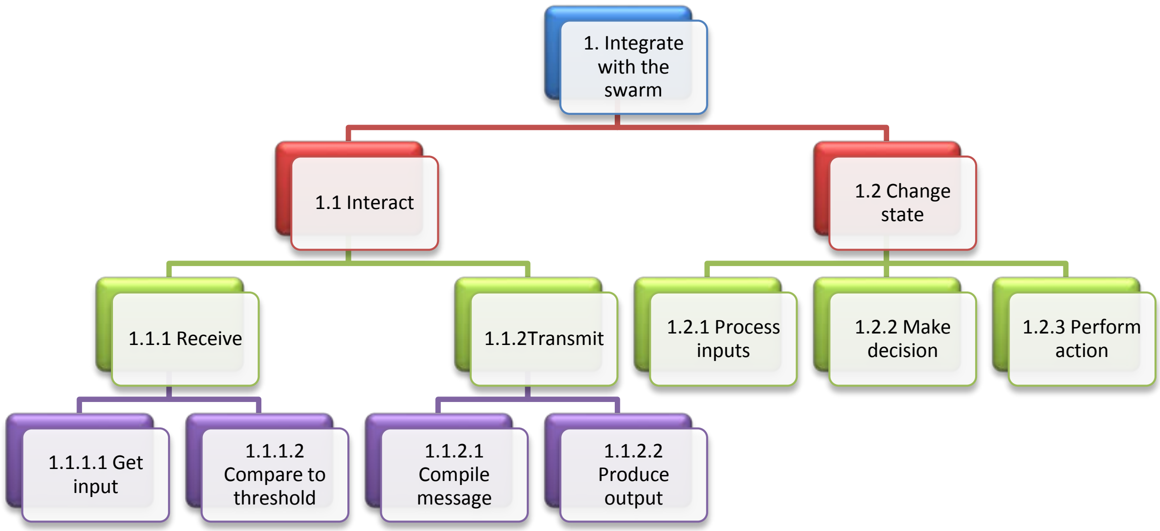

Figure 3 Functional decomposition of an agent in the swarm

The functional decomposition, as shown in Figure 3, begins with the highest level function of an agent in the swarm which is to remain integrated with the swarm (i.e., remain part of the swarm). The following decomposition level is a projection of the swarm decomposition only at the agent level. In order to stay integrated with the swarm, the agent must interact with other agents and change its state according to stimuli from the environment and other swarm agents. Without adapting through state change, the agent will no longer be part of the collective swarm state. In order to interact, the agent must both receive and transmit. Notice that receive and transmit are given in their most general form and do not necessarily imply direct information transfer from one agent to another. These functions also support indirect interactions through sensory stimuli from a change in the environment. The agents' state change is decomposed to its enabling sub-functions: processing input (from other agents or the environment), making a decision based on that information and performing some action according to that decision. Lastly, receive and transmit are decomposed to sub-components as well, where input, output and message refer to either direct information or sensing / creating stimuli from the environment.

The functional decomposition above was used as a reference basis to validate the swarm loss function analysis in the next section. The functional decomposition also helped identify the basic role of interactions through transfer of EMMI (energy, matter, material wealth, and information) in the general integrative model for the swarm discussed in the closing section of this chapter.

E. LOSS FUNCTIONS

A method to quantify the loss presented by a product or system is through the system's loss function with respect to some measure (e.g., performance). According to Taguchi, the overall loss is the quality loss plus the factory loss (in the commercial domain). Quality loss is the loss incurred after the product has been shipped (e.g., customer return due to dissatisfaction). Factory loss is the loss incurred by the factory in order to reach a specified performance target. According to (Taguchi, Subir, & Yuin, 2005):

> Quality loss function is used for the nominal-the-best, smaller-the-better, larger-the better characteristics. The nominal-the-best characteristic is the type where there is a finite target point to achieve. There are typically upper and lower specification limits on both sides of the target. For example, the plating thickness of a component, the length of a part, and the output current of a resistor at a given input voltage are nominal-the-best characteristics.
>
> A smaller-the-better output response is the type where it is desired to minimize the result, with the ideal target being zero. For example, the wear on a component, the amount of engine audible noise, the amount of air pollution, and the amount of heat loss are smaller-the-better output responses. Notice that all these examples represent things that we do not want, not the intended system functions. In the smaller-the-better characteristic, no negative data are included.
>
> The larger-the-better output response is the type where it is desired to maximize the result, the ideal target being infinity. For example, strength of material and fuel efficiency are larger-the-better output responses. Percentage yield seems to be the larger the better, but it does not belong to the larger-the-better category in quality engineering, since the ideal value is 100%, not infinity. In the larger-the better characteristic, negative data are not included.
>
> Quality loss function types can be described by the set Equations (11):

$$\text{Nominal-the-best:} \quad L = k(y-m)^2 \quad \text{where } k = \frac{A_0}{\Delta_0^{\,2}}$$

$$\text{Smaller-the-better:} \quad L = ky^2 \quad \text{where } k = \frac{A_0}{y_0^{\,2}} \tag{11}$$

$$\text{Larger-the-better:} \quad L = \frac{k}{y^2} \quad \text{where } k = A_0 y_0^{\,2}$$

A_0 is the consumer loss and y_0 is the consumer tolerance. Figure 4 displays qualitative plots corresponding to these loss function types. The *y* axis is the loss and the *x* axis is the performance or target value.

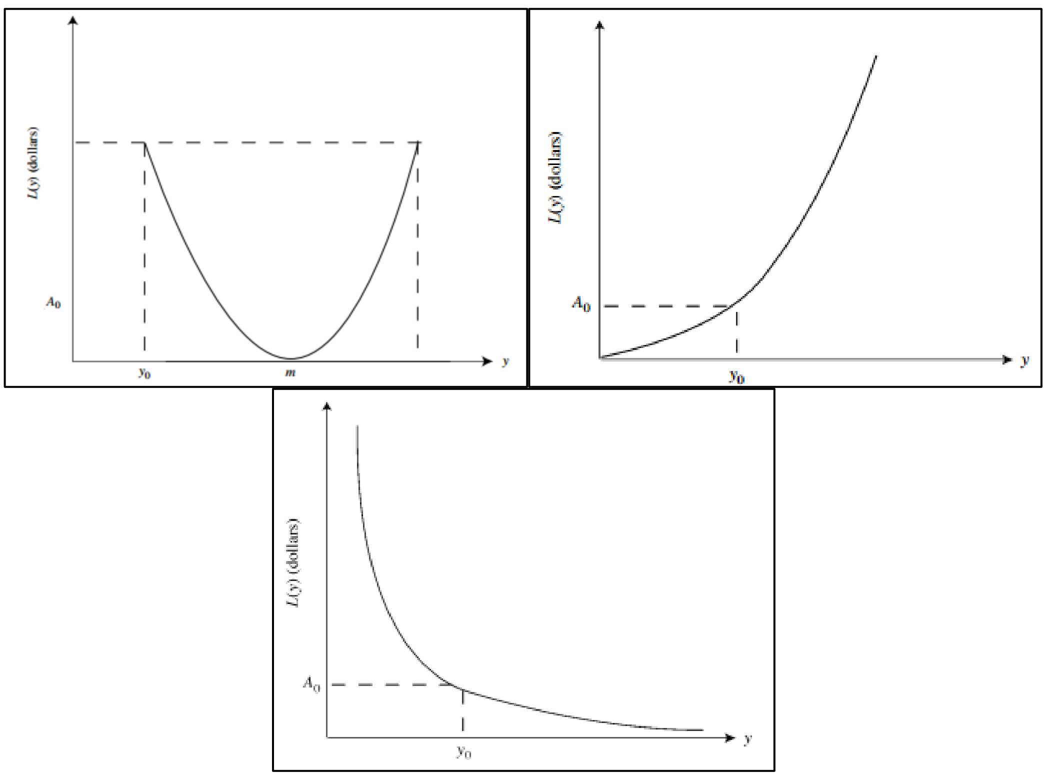

Figure 4 Loss function types. Top row: left - nominal-the best, right – smaller-the-better. Bottom row: larger-the-better. From (Taguchi, Subir, & Yuin, 2005)

The advantage of using these loss functions with respect to requirements conformance is that it allows the quantification of loss according to product / system deviation instead of a binary yes / no conformance criteria.

In accordance to these definitions, a loss function can be used as a metric to distinguish between different swarm types. In order to achieve a certain objective, the agents of the swarm must expend energy. A coordinated UAV attack after loitering was selected as a hypothetical test case to for the loss function. Examination of centralized control versus distributed control reveals different loss functions behavior from the perspective of the swarm and the control function / unit. In Figures 5 and 6, the loss function qualitative plot for the centralized and autonomous control are shown (respectively.) In the centralized case, the swarm is predicted to exhibit a larger-the-better loss function as the agents (UAVs) have no self-knowledge of their proximity to the target, their "willingness" to expend more energy (fuel) as mission time passes will diminish while approaching the no-return point on their fuel sensors. From the centralized operator point of view, energy expenditure can increase as the UAV is nearing its target. These different perspectives on energy loss arise from different situational awareness.

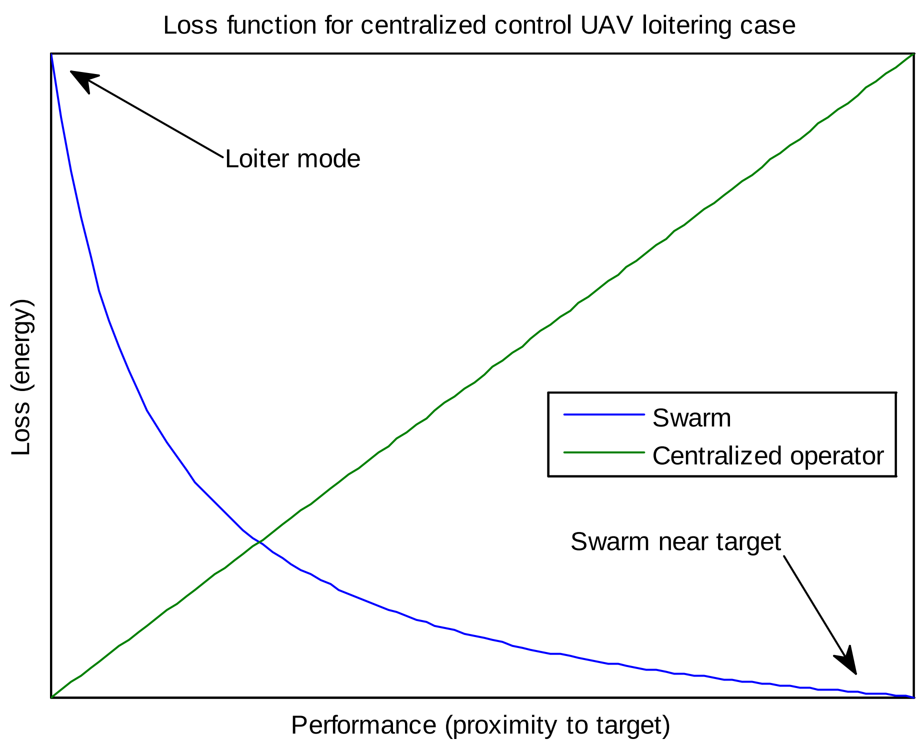

Figure 5 Loss function for centralized control UAV case

In the autonomous case, the swarms "willingness" to expend energy increases on approach to the target (a smaller-the-better loss function). To the extreme, the UAVs maybe sacrificial and therefore their decision mechanism will guide them to the target with knowledge that fuel can be fully expended as long as the objective is attained (or has a high probability of being attained). The operator in this case has no direct control over the UAVs and is therefore more "willing" to witness larger expenditures of fuel at first when the swarm is autonomously searching for the target over an area and has greater reserves. As the swarm approaches the target, the operator will have greater concern of the UAVs loss, as he has no control and possibly knowledge of the situation with respect to the target.

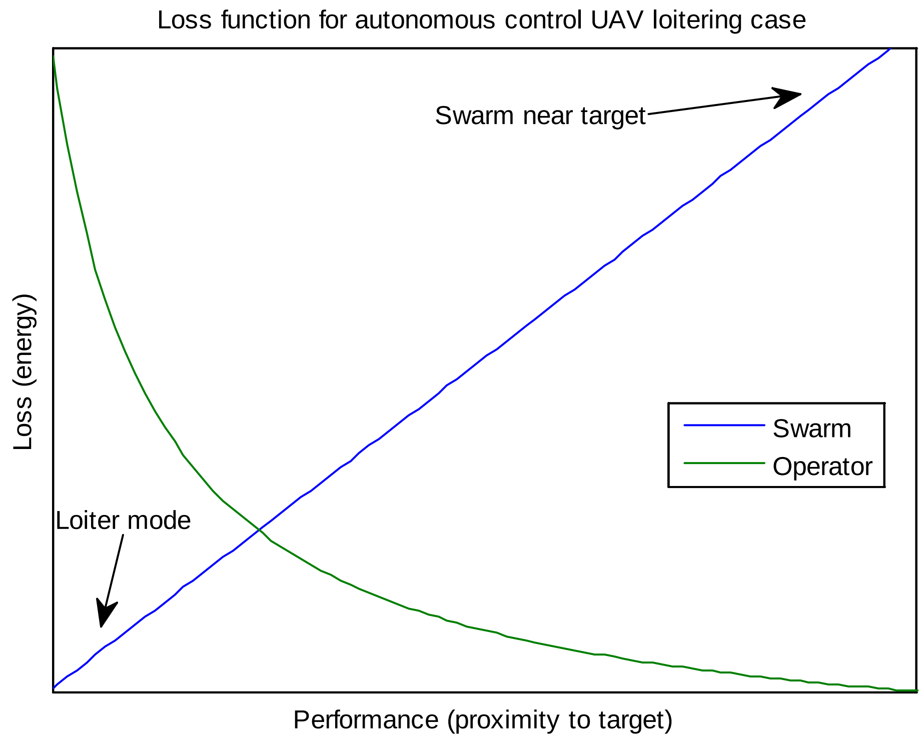

Figure 6 Loss function for autonomous control UAV case

An external observer will only witness the swarm (in blue) loss function. While the comparison of loss functions in these cases is qualitative in nature, it holds potential to be utilized as a categorization tool when observing a swarm with no preliminary

knowledge of its control mechanism. It is also important to mention that the loss function may represent different types of losses, generally categorized into: energy, matter, material wealth and information.

F. INTERACTION VS. INTEGRATION IN COMMUNICATION THEORY

To formalize the proposed integrative model in the next section a better understanding of the concept of integration and its relation to interaction is required. According to (Holmes, 2006) in his book *Communication Theory* a formalized distinction between interaction and integration can be made:

> Whereas interaction involves the empirical act of engaging in a speech act, either extended or in mutual presence, social integration is made possible by some or other form of reciprocity, via interdependence, long term continuity of association and strong identification with another – even an abstract other.

According to the Merriam-Webster dictionary, reciprocity is defined as the quality or state of mutual dependence, action, or influence. In other words, Holmes suggests reciprocity can occur without direct interaction. Holmes continues, and states that most reciprocity involves little direct interaction at all, but is rather embedded and may not be empirically obvious. Also, indirect one time serendipitous interactions do not create reciprocity (e.g., strangers exchanging information on a single event over the Internet). Another important concept introduced in (Holmes, 2006, pp. 151–165) is the perspective of levels of integration which primarily differ in their abstraction in space and time. Examples of these levels are: face-to-face integration, agency extended integration (by representatives) and disembodied integration (constraints of being at one place in one time are overcome by means of technological extension). All integration perspectives displayed in the text show that:

> In each of the levels of social integration, individuals are separated and united at the same time. It is the architecture of this separation and unity and tensions between levels of integration that determine the association possible within given social formations. (Holmes, 2006, p. 165)

G. THE INTEGRATIVE MODEL AND A MAPPING FRAMEWORK TO CONTROL MECHANISMS

Based on previous insights from the functional decomposition, system views, and loss functions an integrative model (a model based on integration theory) could be proposed for the general swarm model. A graphical representation of the integrative model is shown in Figure 7. The model description was developed in association with Gary Langford (Naval Postgraduate School, Monterey, CA, 2012). The model incorporates distinctions between different types of interactions such as internal interactions between swarm agents, interactions with an external command and control object and interactions with the environment. A general swarm model must allow different combinations of these interaction types. Interactions between objects are facilitated through transfer of EMMI (energy, matter, material wealth and information) through the "transmit" and "receive" processes between objects. Each object has an internal control mechanism that represents its internal decision making process. The model is based on a distinction between different levels of integration:

- Interactions – the processes of transmit and receive (as defined in the functional decomposition) are enabled.
- Emergence – occurs due to interactions when a swarm's object traits are changed. Objects have properties (inherent to the object's physical existence. e.g., mass). Objects have traits due to the objects' interaction with the environment (e.g., velocity). Objects have attributes that are changeable (e.g., a UAVs wing color). Emergence is observable when there is a change in objects' traits.
- Integration – EMMI is received by an object that changes the receiving object in accordance to changes in the transmitting object. Changes that are reversible when interactions cease do not show integration rather interactions. Changes that are irreversible show integration. Interaction is possible without integration. Emergence is possible without integration. Integration requires both interaction and emergence.

Control mechanism categories will be established from the integrative model and will be categorized by:

- Their information source: global, hybrid and local.
- Their interactions with: the environment, the swarm (internal) and the C2 unit (external).
- Level of integration: interactions, emergence and integration.

Definitions for information sources terminology as used in the categorization framework are given below:

- Global Information Source:

  Definition 1: Swarm objects change their state in reaction to a common information source

  Definition 2: Swarm objects are equal in their aptitude (fitness) to gain new information regardless of time or space properties associated with them.

- Local Information Source:

  Definition 1: Swarm objects change their state in reaction to individually unique information source [accessible only to them].

  Definition 2: Swarm objects differ in their aptitude to gain new information based on their space and time properties.

- Hybrid Information Source:

  Definition 1: Swarm objects change their state in reaction to a combination of common and individually unique information sources.

  Definition 2: Swarm objects marginally differ in their aptitude to gain new information based on their space and time properties.

Figure 7 also shows a high level representation of how to translate the theoretical swarm integrative model into the MANA simulation environment. Further practical translation of the integrative model framework into the MANA environment is discussed in more detail in the next chapter. Interaction levels will be simulated based on a local rule set that is independent of other swarm agents. Emergence will be simulated through deterministic agent rule sets that react (i.e., are dependent on other agents states). Integration will be simulated through the use of trigger states that will change an agent's internal rule set according to stimuli received by other agents changing states. This change in the internal agent's rule set represents an irreversible change in objects caused by interaction with other objects. It is important to note that real integration is not possible in the simulated MANA environment, due to the deterministic nature of the change in rule sets. While the concept of rule set change is faithful to the concept of integration, in practice, the change is reversible due to the pre-determined trigger that

stimulates the agent's behavioral change. Despite this fact, the display of movement patterns in MANA will allow the research of the transition between integration levels.

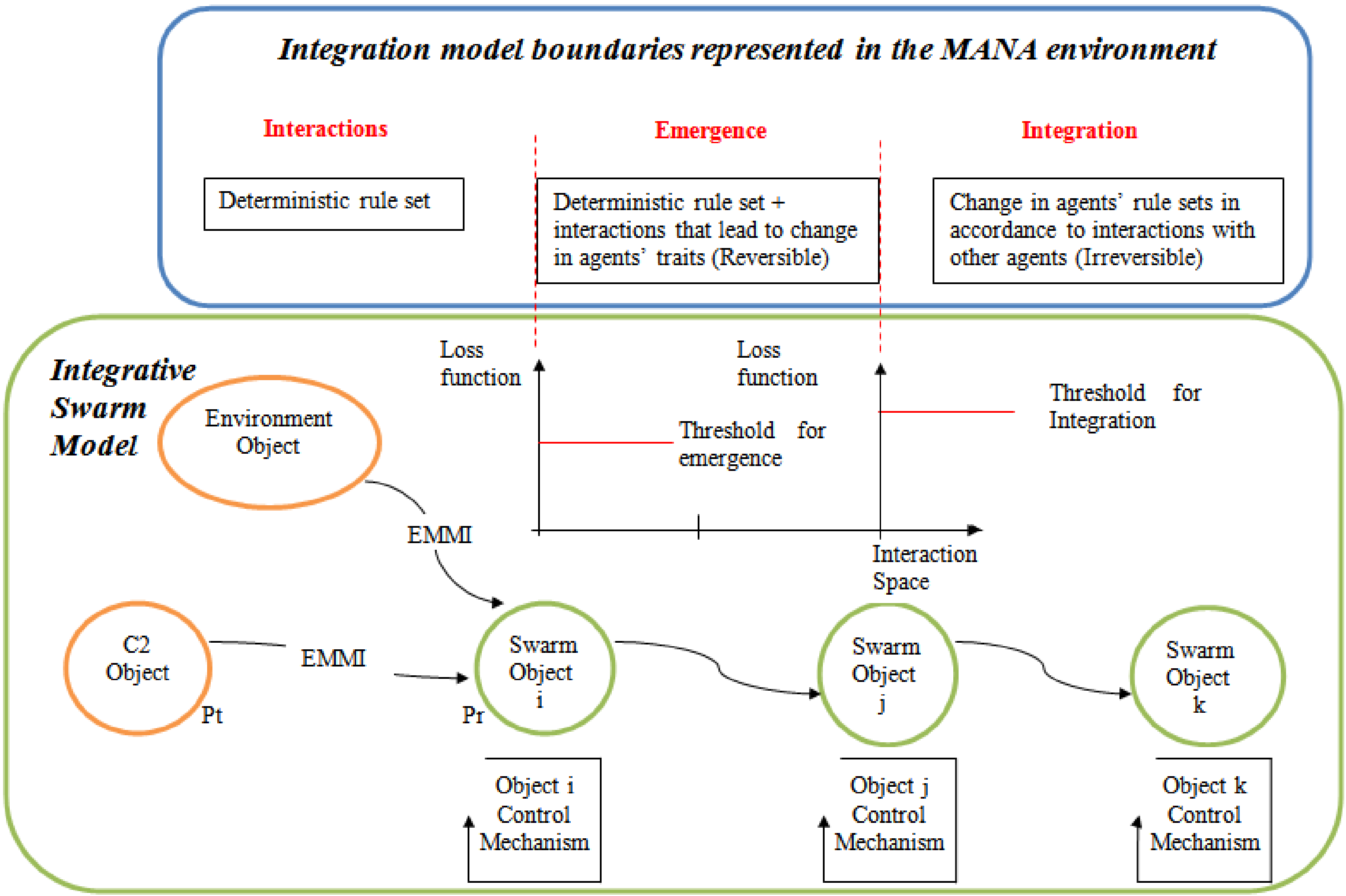

Figure 7 An integrative model for the swarm.

VII. INTERPRETATION OF A SWARM FROM AN AGENT BASED MODEL (MANA)

A. WHY USE MANA?

The MANA agent based modeling environment was selected as a test bed for different swarm control mechanisms. As discussed in the literature review, MANA allows for fast exploration of different emergent behaviors arising from different local rule sets. MANA also incorporates a built-in data recording capability and a basic statistical analysis capability. For this research, the movement patterns of the agents in the swarm are of interest. MANA's recording capability allowed for extensive analysis of agents' positions and movements per time step in the test scenario. The analysis of the raw output data was done in the MATLAB software environment.

B. APPROACH AND METHODOLOGY

In order to test the feasibility of categorizing a swarm into different control mechanisms based on observations of its movement pattern, different scenario test cases had to be established. These test cases aim to represent the basic swarm coordination rules as initially observed by Boid and discussed in the literature review (Fisher, 2009): attraction, avoidance and alignment. Further research of more advanced behaviors can then be based on the analysis of these basic building blocks for movement coordination.

1. Mapping Control Mechanisms to the MANA Environment

Based on the integrative swarm model presented in the previous chapter, a mapping framework of control mechanisms categories can be achieved by establishing what underlying source of information the observed swarm possesses, what types of interactions it has, and the level of integration it displays. Table 4 presents only the interaction types and information source categorization. Table 4 presents interactions based on EMMI transfer, including information transfer through the "transmit" and "receive" processes of communication and energy through the agent's sensors (e.g., a visual stimulus from the environment). It does not yet include how the agent acts in accordance to that information, which will determine the level of integration.

The level of integration (i.e., interaction / emergence / integration) is another dimension in the mapping framework, meaning each one of the rows in Table 4 below may show any one of the levels of integration, given the necessary (but insufficient) condition of interaction.

As a reminder, the information source sub-categories were global, hybrid, and local. The interaction types included the environment, internal swarm agents and the C2 command unit. MANA is especially built to accommodate for network centric warfare through different situational awareness (SA) schemes: Agent based SA, Squad based SA, and Inorganic SA. These SA schemes fit perfectly to simulate different information sources. By using personality movement weights based on different combinations of SA, we receive a set of possible information sources and interaction types. Table 4 shows a mapping from control mechanisms categories to information sources and interaction types. Each category is presented with its respective representation through a MANA SA combination.

New category name	Information source	A.K.A	Interaction type (communications)	Agent SA	Squad SA	Inorganic SA
1. Local	Local	"Distributed"	Environment and internal swarm-objects. (no communications)	X		
2. Internal hybrid	Hybrid	"Hybrid"	Environment and internal swarm-objects (with communication)	X	X	
3. External hybrid	Hybrid		Environment and external C2 object (with communication)	X		X
4. Global internal	Global	"Centralized"	Internal swarm-objects (with communication)		X	
5. Global external	Global		External C2 object (with communication)			X
6. Full Global	Global		Internal swarm-objects and external C2 object (both with communications)		X	X
7. Full hybrid	Hybrid		Environment and internal swarm-objects and external C2 object (both of the latter with communications)	X	X	X
8. Blind	None		None			

Table 4. Mapping control mechanisms categories to MANA SA combinations based on the integrative swarm model

Test cases for different scenarios in MANA focused primarily on control mechanism categories 1, 2 & 4 (A.K.A Distributed, Hybrid and Centralized). These categories yielded substantial insights into the observable patterns differentiating between the control mechanisms. Further expansion into the dimension of level of integration was later achieved by implementing trigger events in MANA that enabled agents to change their rule sets.

2. Analysis Goals

The defined scope of this research was to look at the capability of an external observer to unveil different C2 aspects of a tactical swarm, based solely on the swarm movement patterns. Therefore, the analysis performed using the MANA and MATLAB tools focused on the following goals:

- Display the capability to differentiate different information sources.
- Display the capability to identify when integration is present in the swarm.
- Suggest methods to distinguish between external C2 and autonomous agents.
- Given range-constraint communications and control:

    Display a possible triangulation method to estimate the location of a centralized LOS control unit based on swarm movement patterns.

    Suggest possible methods to estimate the range constraint of a given distributed control (autonomous) swarm. (This final goal was not studied in the time frame of this research).

C. MATLAB INFRASTRUCTURE AND ANALYSIS METHODS

Using MANA's recording capability, a file containing all the raw data of agents' positions over the simulation time steps was obtained for each simulated scenario. This raw data file was then imported as a data array into the MATLAB environment. From this point, the raw data of each scenario could be analyzed using various methods:

- Statistical methods such as correlation, moving average, population mean and standard deviation were used to analyze the swarm agents and the swarm as a whole.

- Physics based concepts such as spatial entropy, fractal dimensions, field potentials and spatiotemporal structures could be implemented to view the swarm as a whole.
- Optimization for triangulation purposes were used to estimate a LOS command source location.

In this section, a short explanation of the more complex methods implementation is given.

1. Speed Correlation

Based on each agents' position in each time step, a velocity vector for that agent could be obtained (time step=1 sec). After obtaining the velocity vectors for all agents, a correlation Matrix A could be built where Aij= the correlation between the velocity vector of Agent i and Agent j. A is obviously a symmetrical matrix. Aij values vary continuously from +1 to -1. A value of +1 (perfect correlation) is translated as perfectly synchronized velocities changes (in time and factor). A value of -1 (perfect inverse correlation) is translated as opposite perfectly synchronized velocities changes in each time step. A value of 0 is translated as no speed correlation.

2. Spatial Entropy

As explained in the literature review, spatial entropy is used in image processing and to track the dynamics of clustering. Spatial entropy can be used to measure how well items or swarm agents are clustered in different spatial scales (Bonabeau, Dorigo, & Theraulaz, 1999, p. 154). For a certain spatial scale s, the related spatial entropy for that scale is given in Equation 12:

$$E_s = \sum_{i \in \{s-patches\}} p_i \log p_i \qquad (12)$$

In Equation (12), p_i is the fraction of all objects on the lattice that are found in s-patch i. Spatial entropy decreases as clustering proceeds (as the system is "gaining order") and thus can be used to identify different clustering strategies timing in different scales.

In the MANA simulation (and MATLAB analysis) the lattice and objects are represented by the 2-dimensional image of the swarm agents' positions in a specific time

step. The entropy value is calculated for each time step image and then plotted over time. Note that the entropy values are normalized to the original pattern (or image) viewed at time step = 0.

3. Fractal Dimensions

As explained in the literature review, in real-life observations, scaling units and ratios are unknown in advance. The use of slope limits on log-log plots of scale to size are used to estimate the fractal dimension. Several different definitions exist, but in this thesis, the one used is the "Box Counting" / "Capacity" dimension definition (Weisstein, 2012) as shown in Equation (13). This definition is suitable for implementation on an image matrix in the MATLAB environment.

$$D = -\lim_{\varepsilon \to 0} \frac{\log N}{\log \varepsilon} \tag{13}$$

In this thesis the "boxcount" package for MATLAB (Moisy, 2008) is used to develop time dependent fractal dimension plots. The initial computation computes how many squares (boxes), of a certain size, are required in order to "cover" the entire pattern displayed by the swarm image in a given time step. Then, the results are shown on a log-log scale of number of boxes required versus the box size. This plot is iterated for each time step image. The slope of the log-log plot for a given box size represents the fractal dimension for that scale. If the fractal dimension remains relatively constant over a certain scale region, the pattern (the time step image) is said to have fractal properties for that region. Once again, this fractal dimension vs. scale is re-iterated for different time steps. After the latter plot is completed, the scale region that displays fractal properties can be selected, and the respective fractal dimension for that scale can be plotted as it changes over time with the swarm pattern changes.

4. Spatiotemporal Structures

According to the literature review, self-organized phenomena have a basic characteristic of creating spatiotemporal structures in an initially homogeneous medium. In order to recognize this characteristic in a dynamically changing swarm pattern, an image that transcends time and space is required. In the MATLAB environment, this was

practically obtained by summation of the time step images of the swarm patterns. The resulting image summation represents how many times a single cell in space (or a pixel) was “visited” (or populated) by the swarm agents. The resulting image shows interesting structure formations that are clearly distinguish (by shape, density and dispersion) the different compared control mechanisms.

5. Field Potential

As was noted in a survey of literature discussing swarm behavior, self-organized phenomena have another basic characteristic of several stable states. This research hypothesized that while agents move through space over time, their combined trails may help identify global or local potential fields. Given sufficient agents moving in space, these fields can be “drawn” with sufficient resolution to unveil local and global attractors and repellents of the swarm collective. Initial work was made on the “Rally” scenario, but had very limited results for presentation at this moment. One of the limiting factors for this method was that at any given moment in time, an agent’s trajectory was established based on its local sensor. Therefore the perceived “potential” fluctuates, not due to actual changes in the environment, but due to changes in the agent’s perception. This limitation obviously varies based on the agent’s information source and sensor range.

6. Moving Standard Deviation of Speed as a Measure of Autonomous Agents in the Swarm

Control mechanisms of autonomous unmanned systems are characterized by the use of feedback control systems. The implemented transfer functions response to external input will usually display some overshoot and settling time until the desired command is achieved. It was assumed that a swarm agent interacting and responding to the existence of other swarm members would display some fluctuation around a general trajectory (e.g., to maintain distance) due to these inherent characteristics of the feedback control mechanisms. These fluctuations differed from the case of a centrally controlled swarm, in which agents can maintain formations by predefined stable trajectories. A centrally controlled swarm (with a global information source) was identified by the speed

correlation matrix described in Item 1. An additional way to distinguish the autonomous agent was based on the agents fluctuating speed behavior and thus did not require an approach comparing to other swarm members. By using a moving standard deviation (STD) of an agents' speed a threshold was set for the STD that was considered as controlled. That is, if the agent maintained a speed STD lower than the threshold for a certain time period it was considered as externally controlled. The window used for the moving STD calculation should be long enough to assure speed is indeed maintained and not too long, so as to allow for the case of direction change in a controlled agent.

7. Optimization for Triangulation

After establishing a method to detect whether a swarm was controlled by an external C2 unit, there were cases in which that C2 unit was in close range (e.g., within Line of Sight (LOS) for control channel). In that case, it was possible for the defender to triangulate the source of the swarm control unit by observing the swarm's movement patterns. The point in time in which an agent had transitioned from autonomous mode to controlled mode was established via the method described in Item 6 above. Given an agent's transition, one was able to establish that the agent had been given an external command and thus has entered the range of the control unit at that moment or with some command lag. For sake of simplicity, and within the MANA limitations, we assumed the agent was given the command as he crossed into the limiting range of the control unit (that is how the scenario was implemented in MANA). Despite that simplifying assumption, there was still a possible lag between the time of command and the observable transition (e.g., due to processing and inertia moments).

The transition locations of several agents were used to triangulate the source of command by applying constraint that stated all transitions must occur in the specified limiting range. For every possible command source location in space, a value was given according to an objective function. The objective function utilized a Matrix O, where Oij = (range from agent *i* to the possible command source location) - (range from agent *j* to the possible command source location). The objective function was the sum of all the matrix elements. By searching the minimum (optimum) of the objective function, the

difference in estimated ranges decreased. In a perfect situation, the objective function would reach zero when all ranges are equal (the case of a perfect circle as transition locations and the estimated command source in its center).

Obviously, the minimum solution will not be perfect due to different lag times. For further optimization, the algorithm looked into past locations (assuming a common lag) to find when the STD between estimated ranges was the smallest. The analysis showed that this method corresponded to the minimum error from the actual source location.

In addition, the analysis showed that as the number of agents used for triangulation increased, the estimated location error decreased. In a sense, this dependence of estimation accuracy on swarm numbers links to the collective intelligence concept shown in the literature review of swarms. In this case, we exploited the swarms' collective information to gain a better estimation of the command unit location. The swarm, by sheer numbers, corrects our inherent inaccuracy (due to unknown time delays) by averaging of estimations. So the basic property of the swarm that gives it scalability and robustness can be turned against it.

D. ANALYSIS OF SCENARIOS AND RESULTS

Scenarios were developed based on the stated goals for the analysis. Some goals were studied using several test cases and different methods.

1. Differentiating Information Sources

By using the framework shown in Table 4, different control mechanisms (i.e., "distributed", "hybrid" and "global") were created for the "Rally" and "Avoid" scenarios described below. These control mechanisms differ in the swarm's information sources. By using the different methods described in Section C to study these control mechanisms under different scenarios, differentiating metrics were established.

The "Rally" and "Avoid" scenarios display the basic coordination rules of avoidance, attraction and alignment. The assumption made in both scenarios was that the

agent sensory range is smaller than the entire area of interesting stimulus, otherwise there would be no way to differentiate if the information source is from the agent's local sensors or a global source.

a. The "Rally" Scenario

The "Rally" scenario tests the swarm's movement patterns when a rule set of attraction to other squad friends (i.e., swarm agents) is put in place. A swarm of 200 agents was set up in random locations on a 1000x1000 cells *x-y* plane. Each agent's sensor range was 100 cells. The personality weights for different agents were assigned based on the framework shown in Table 4 and are displayed in Table 5. The distributed category is based on Agent situational awareness (SA) weights only. The centralized category was based on Squad SA weights only. The Squad situational awareness was a common source of information to all swarm agents that integrates the information from all agents' sensors. Finally, the hybrid category was based on both Squad and Agent SA weights.

Category name	Information source	A.K.A	Personality property	Agent SA	Squad SA
1. Local	Local	“Distributed”	Attraction to squad friends	10	0
2. Internal hybrid	Hybrid	“Hybrid”	Attraction to squad friends	5	5
3. Global internal	Global	“Centralized”	Attraction to squad friends	0	10

Table 5. Personality weights for the “Rally” scenario

The unfolding of the “Rally” scenario for all three categories is shown in Figure 8:

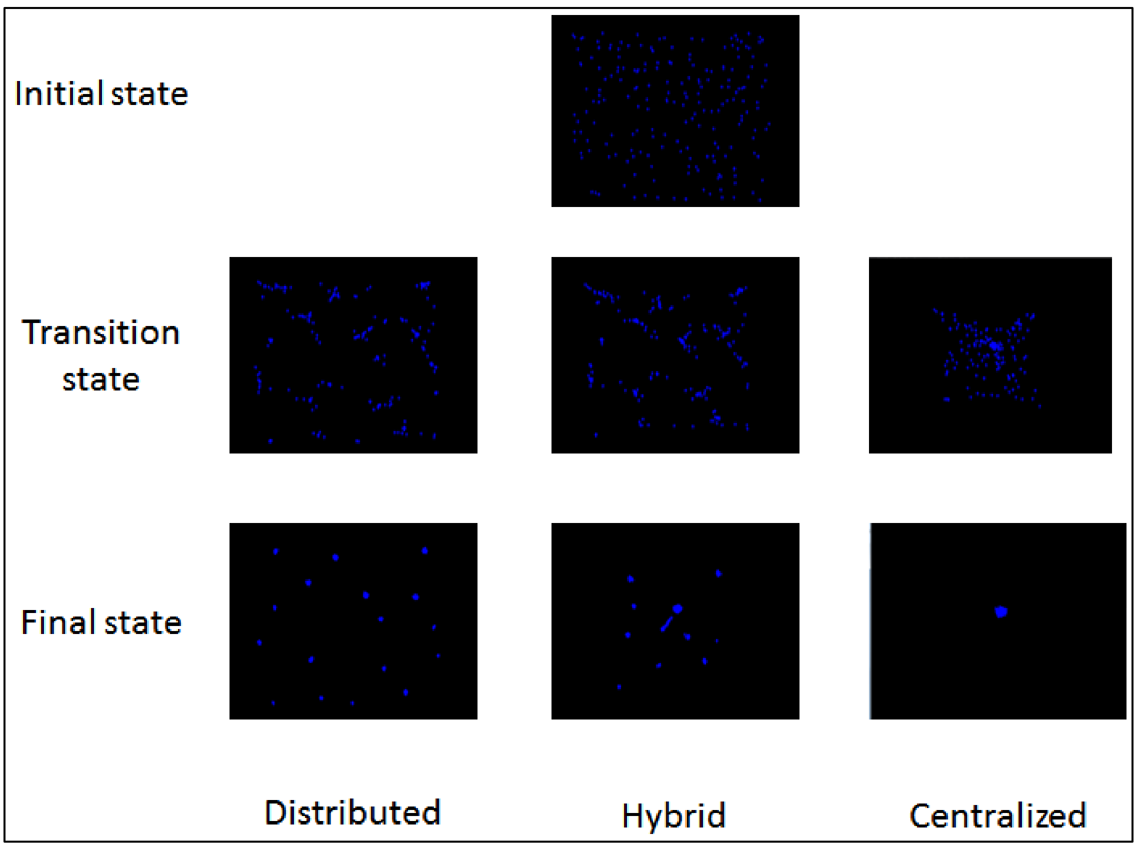

Figure 8 MANA frame shots of “Rally” scenario

The distributed category shown in Figure 8 shows a final state of several clusters due to the local information viewed by the agents. The Centralized category shows one cluster with all agents clustered together based on their common SA. The hybrid case shows several clusters that are denser than the distributed case. The hybrid final state is only marginally stable, as the agents were aware of the other clusters; slow movement of the clusters toward one another was observed.

The “Rally” scenario was analyzed using the methods described in Section C. In Figure 9, selected agent routes are plotted over time for the 3 categories. From the figure, it is clear that agents in the centralized category move in straight trajectories towards their final goal. The distributed agents moved to their local clusters with slight adjustments, due to changes in local information observed by their sensors. Finally, the hybrid agents move to clusters as well, but for longer distances and curved trajectories that are effected by a combination of sources of information input.

Analysis of the agent’s speed correlation (for the x and y components) with respect to other agents is shown in Figure 10. Each cell Aij in the colored matrix represents the correlation of speed vectors between Agent i and Agent j. The matrix is symmetrical and the main diagonal equals 1, by definition. Figure 11 shows the same analysis for the absolute speed (i.e., the speed magnitude with no consideration of directionality). From both Figure 10 and 11, higher correlation for the centralized case is noticeable. It was difficult to distinguish any difference in correlation between the hybrid and distributed case. In comparison, the “Avoid” scenario exhibited extreme differences between these 3 categories.

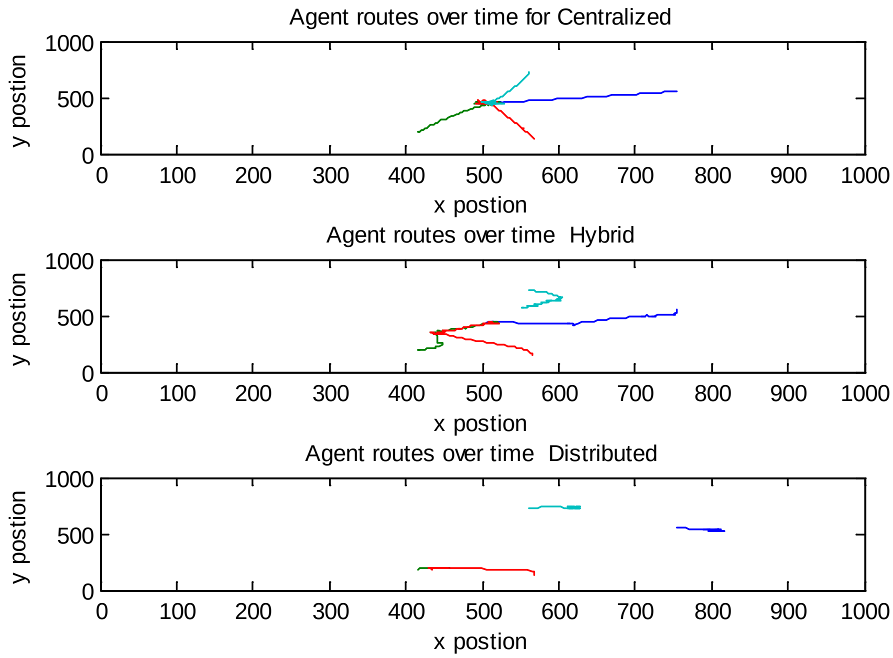

Figure 9 Agents' routes over time for the "Rally" scenario.

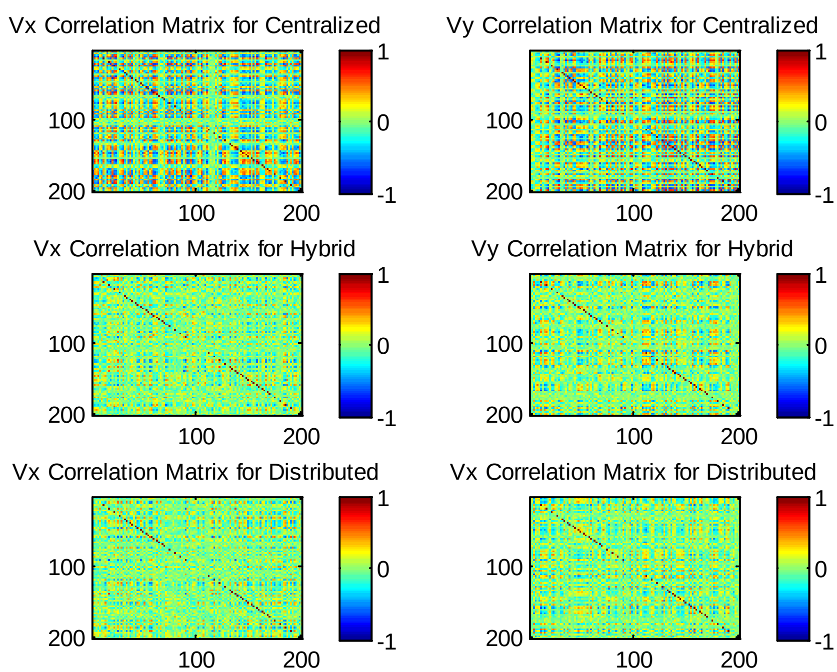

Figure 10 Speed components correlation for the "Rally" scenario.

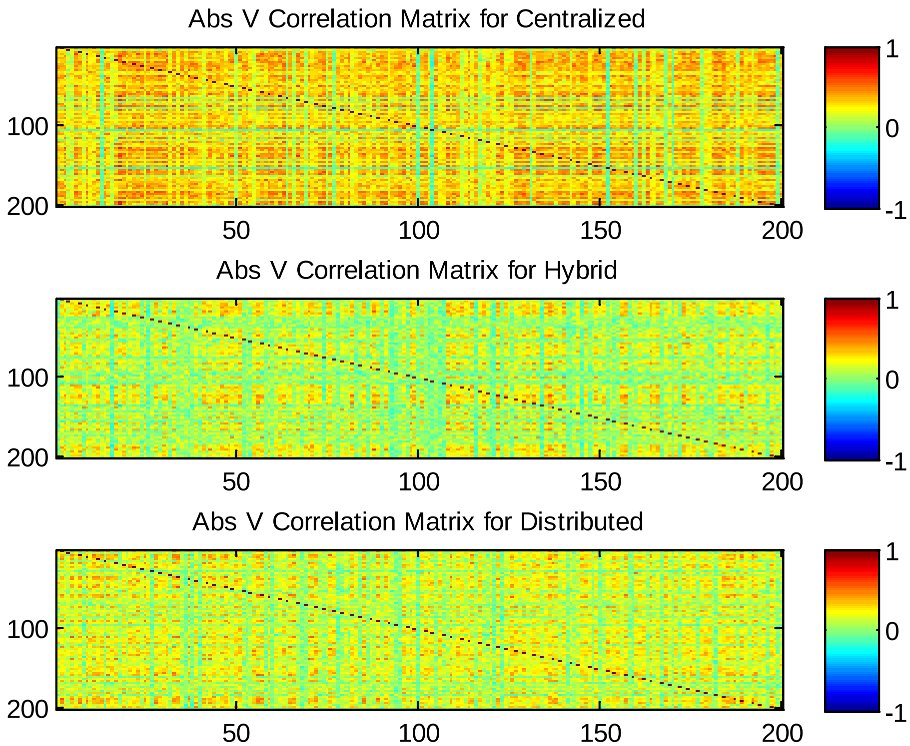

Figure 11 Absolute speed correlation for the "Rally" scenario.

In the next step of the "Rally" scenario analysis, the spatiotemporal method described in Section C was performed. The resulting images can be seen in Figure 12. As a reminder, the spatiotemporal image is the summation of the swarm pattern (agent locations) per time step over a defined time period. The resulting image shows how many times a location in space has been visited by swarm agents (equivalent to a cell "counter"). The produced image highlights spatial patterns formed over time (i.e., highly "visited" locations will appear brighter). The image color bar was truncated at the value of 6 to better stretch the dynamical range of the color map. So, the portions showing red color at the cluster centers may actually have slightly higher figures attached to them. The centralized case showed no structure formation besides the center cluster. The distributed case showed only the multiple final stable clusters. The hybrid case, on the other hand showed "streams" which related to common routes taken by several

agents. The local information source "drew" the agents together; and from there, the global information source drew the formed clusters to the optimal center solution. This cluster movement is the reason for the "streams" structure observed.

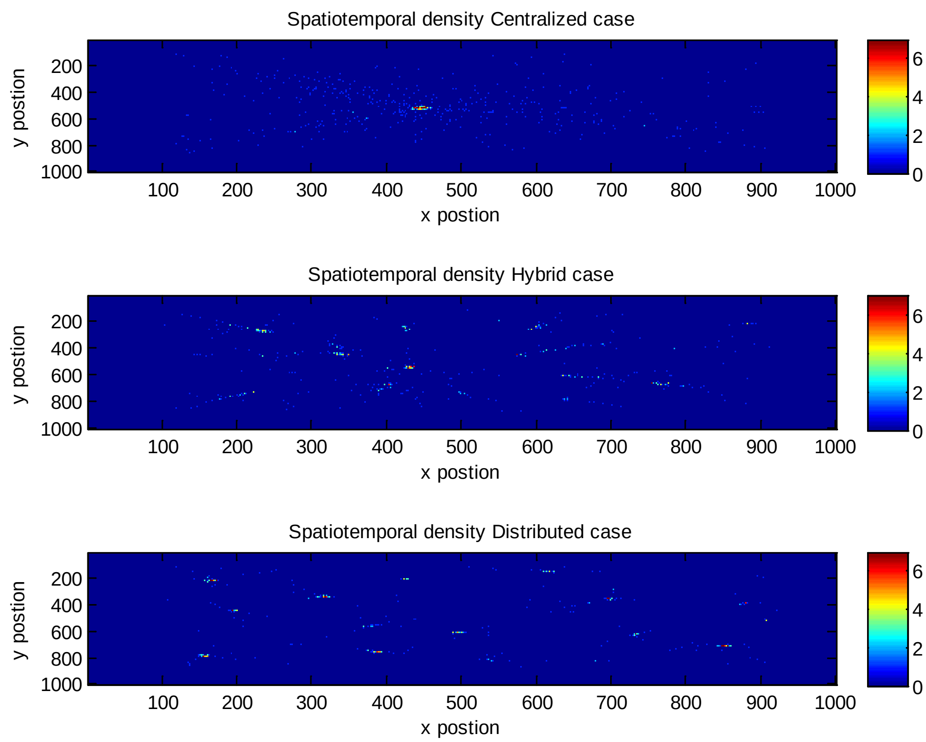

Figure 12 Spatiotemporal density for the "Rally" scenario.

Looking at the swarm as a system from a macroscopic view makes it possible to use system measures such as spatial entropy and fractal dimensions in order to further understand swarm dynamics. The normalized spatial entropy of the swarm over time is plotted in Figure 13. As the swarm created clusters, the entropy measure of the swarm, for all cases, decreased down to a finite value (based on the final cluster size). The distributed and hybrid cases exhibited similar multiple cluster formations (at the final simulation step) and therefore exhibited similar final values. The hybrid case showed slower clustering and therefore its entropy decreased more gradually. The centralized case clusters to a single area and therefore showed lower entropy values.

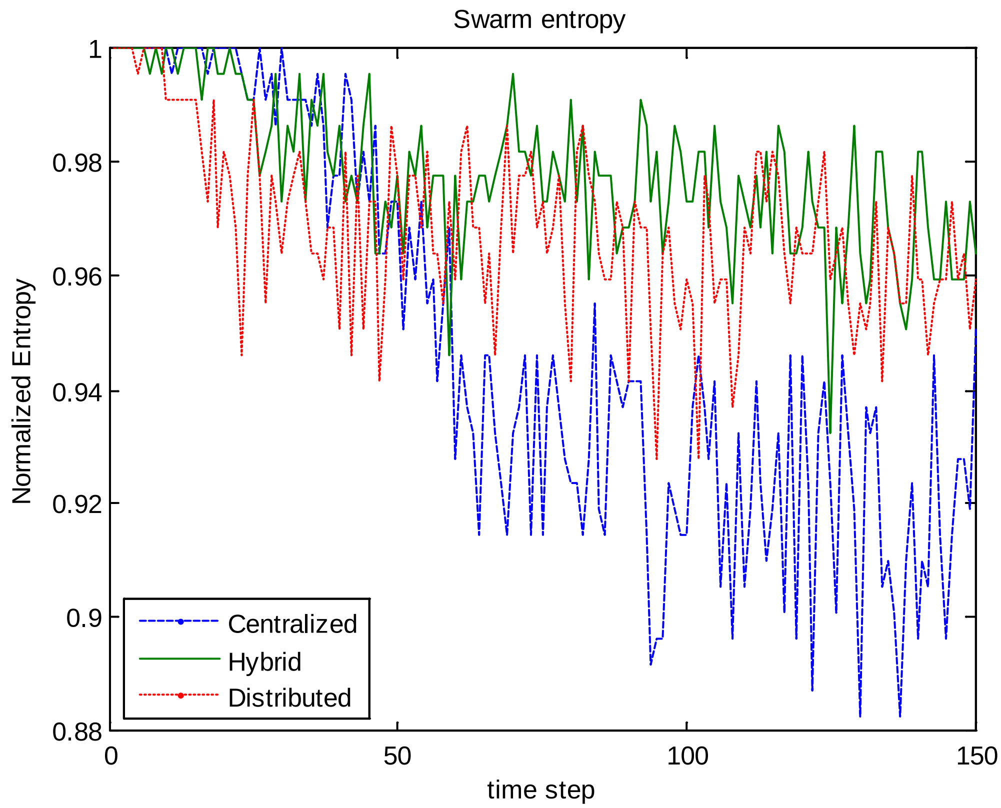

Figure 13 Spatial entropy over time for the “Rally” scenario.

Figure 14 displays the fractal dimension plots for each time step. On the left column, the log-log plots of number of boxes vs. box scale is plotted. Each color represented a pattern of a single time step. The right column showed the slope of the log-log plot vs. scale. The slope values shown in the left column are, by definition, the local dimensions for that scale. Around the scale of 10^1 box size, a constant local dimension was observable. This fact suggests that our swarm exhibited some measure of fractal properties for this scale. In the time-dependent-fractal-dimension plots, the mean dimensional value around this scale is used. Once again, note that each color in the right column represented a pattern of a single time step. Even before plotting the fractal dimension over time, it was noted that the centralized case displayed much higher variability of local dimensions across various scales.

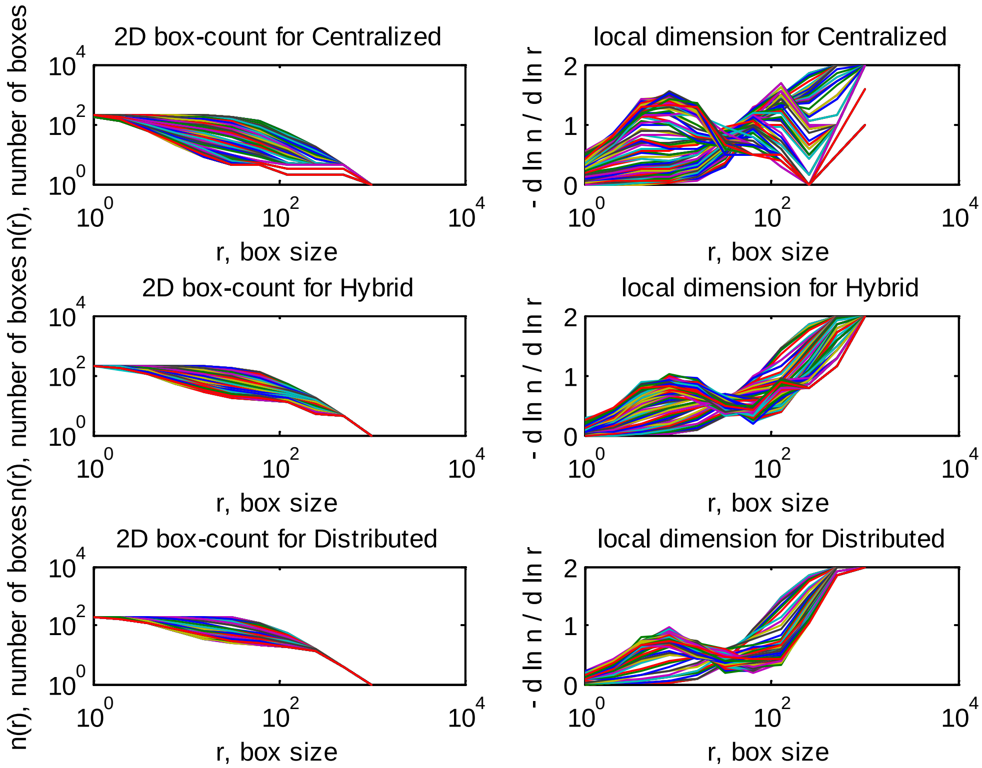

Figure 14 Box counts and local dimension plots for the “Rally” scenario.

Figure 15 displays the fractal dimension over time for the three categories, based on the information showed in Figure 14. The distributed case showed a steep incline to its final stable dimension. This behavior was due to the relative proximity of other local cluster members of the swarm. The centralized case initially showed lower incline. The centralized swarm agents gained speed over time and thus the slope increased. Eventually, the centralized swarm showed a higher final dimension than the distributed case. Once again, that was due to the area coverage of the single final cluster solution. The hybrid case showed a marginal slope between the extremes. It also reached a similar dimension as the distributed case, but we can see that it was not stable and there was a slow increase due to the clusters movement toward one another.

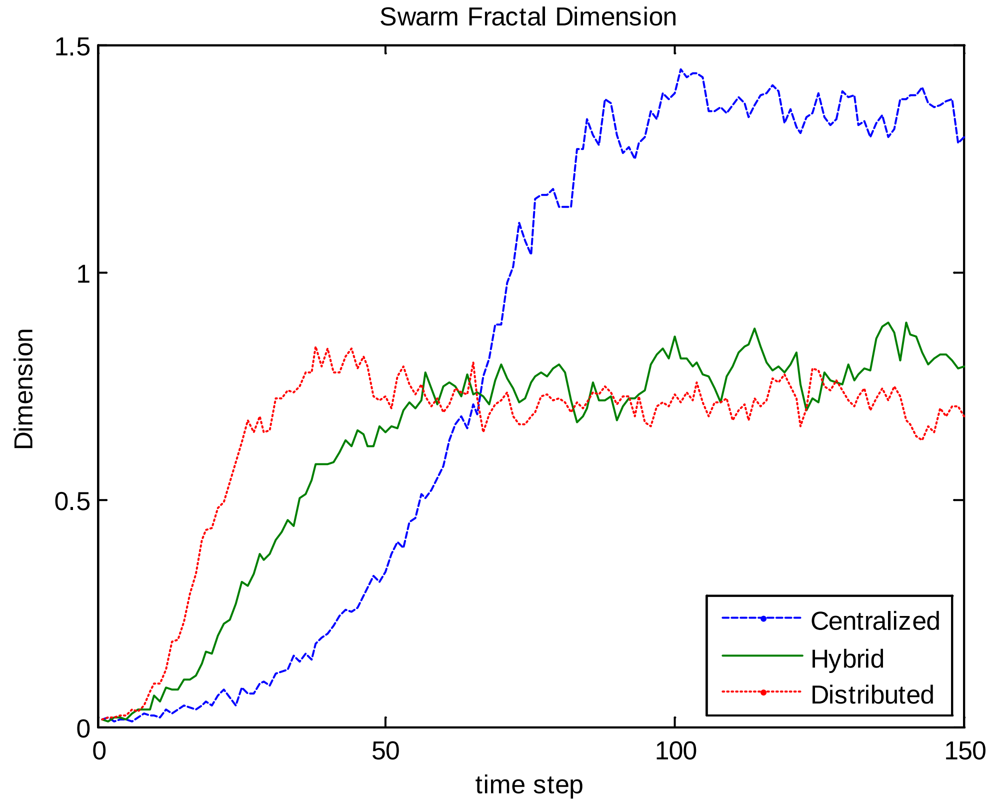

Figure 15 Fractal dimension over time for the "Rally" scenario.

As discussed in the literature review, initial attempts to utilize the swarm agents' routes over time to capture a visual display of the potential field perceived by the swarm members were made. At the time of writing of this thesis, these attempts were made only on the centralized case due to the global information presented in this case. Figure 16, shows the resulting potential figure, with the inherent assumption of a radial point-source field, as all agents were attracted to the center mass of the swarm. The final location for each agent was assigned a minimum value of zero and all other values were simply assigned a value based on distance. That assumption related to a $\phi \propto kr$ potential form, which came from the constant force (of attraction) exerted by objects in the MANA simulation (i.e., force of attraction is range-independent and constant as long as the object of interaction is inside the agents' sensor range).

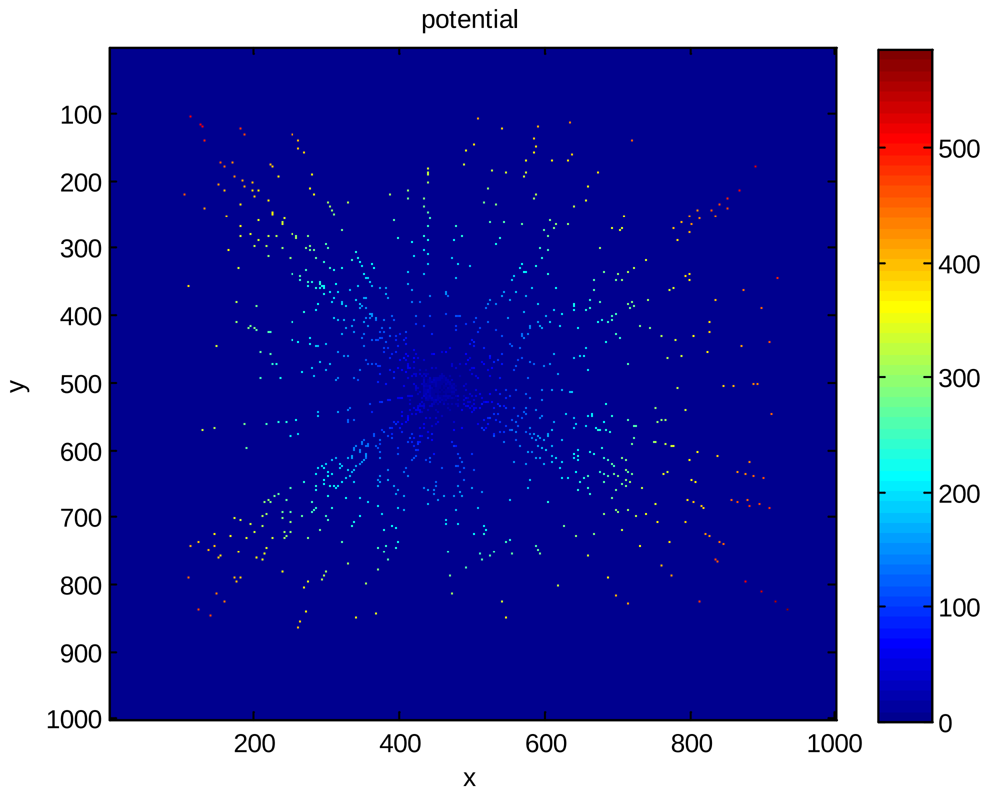

Figure 16	Potential field display for the centralized case in the “Rally” scenario.

b. The “Avoid” Scenario

The “Avoid” scenario tested the swarm’s movement patterns when a rule set of avoidance (repellence) of an enemy unit was used while the agents attempted to reach a predefined destination. A swarm of 100 agents was set up in random locations inside a predefined 200x250 staging area, as shown in Figure 17. The entire simulation area included 1000x1000 cells in the x-y plane. Each agent’s sensor range was 100 cells. The personality weights for different agents were assigned based on the framework shown in Table 4 and are displayed in Table 6. The distributed category was based on agent situational awareness (SA) weights only. The centralized category was based on squad SA weights only. The squad situational awareness was a common source of information to all swarm agents that integrated the information from all agents’ sensors.

Finally, the hybrid category was based on both squad and agent SA weights. It was important to note that a negative personality weight related to the avoidance from (instead of attraction to) the enemy agent.

Category name	Information source	A.K.A	Personality property	Agent SA	Squad SA
1. Local	Local	"Distributed"	enemy agents	-10	0
2. Internal hybrid	Hybrid	"Hybrid"	enemy agents	-5	-5
3. Global internal	Global	"Centralized"	enemy agents	0	-10

Table 6. Personality weights for the "Avoid" scenario

The unfolding of the "Avoid" scenario for all three categories is shown in Figure 17.

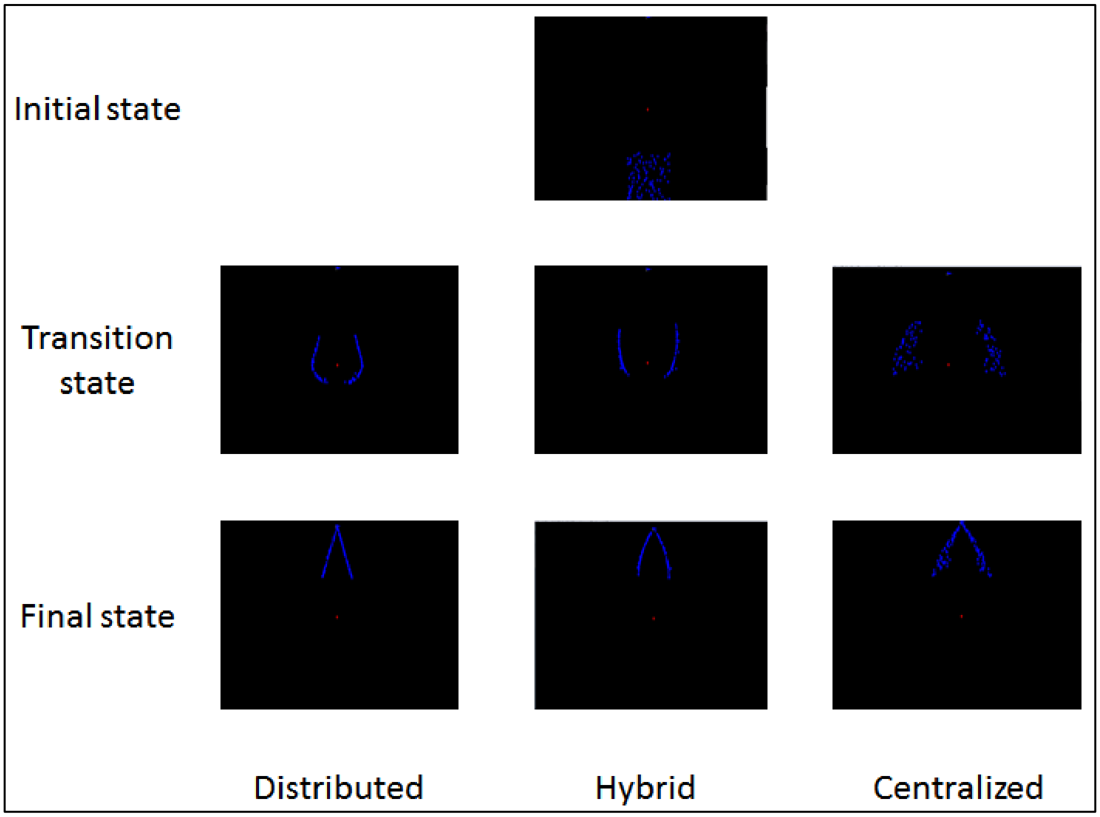

Figure 17 MANA frame shots of "Avoid" scenario

The distributed category shown in Figure 17 shows a tight formation circling the avoided enemy unit. This tight formation was due to the local information viewed by the agents (i.e., the agents react only when the enemy unit was in sensor range). The Centralized category displayed a split into two groups of dispersed agents. The centralized swarm agents reacted to the global, common information source and therefore reacted the moment the first agent detected the enemy in sensor range. The hybrid case showed a combination of both behaviors. A tight formation was observable due to local information source decision making. The formed column was curved due to the fact that agents continued to react to the enemy unit even after it had left their sensor range. The hybrid swarm movement was a combination of agent speed component and a group speed component.

In Figure 18, selected agent routes are plotted over time for the 3 categories. From the figure some interesting geometrical properties are observable. The

centralized swarm agents showed varying routes that display discontinuities due to reoccurring swarm reactions to a single agent's discovery of the enemy. The distributed agents showed almost identical routes (depending on initial start location). Route similarity was explained through the localized sensor base information (for a given point in space, any agent makes the same decision). Finally, the hybrid agents showed a smooth yet curved route varying in curvature radius. This shape was the result of two forces acting on the agent (global and local).

Analysis of the agents' speed correlation (for the x and y components) with respect to other agents is shown in Figure 19. From Figure 19, the x direction speed component displayed absolute perfect correlation for the centralized case (due to a collective swarm reaction to the input global information). The hybrid case showed marginal correlation (based on a combination of local and global decision making). Finally, the distributed case showed little to no correlation of speeds. The y speed component was not relevant in this case due to the predefined final destination given to all swarm agents that committed their speed in the y direction.

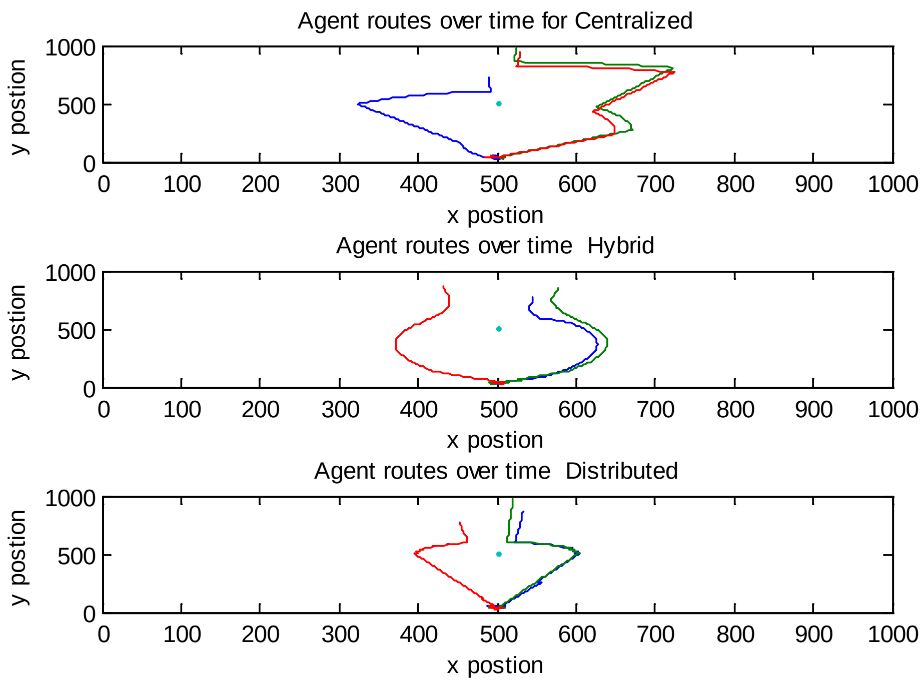

Figure 18 Agents' routes over time for the "Avoid" scenario.

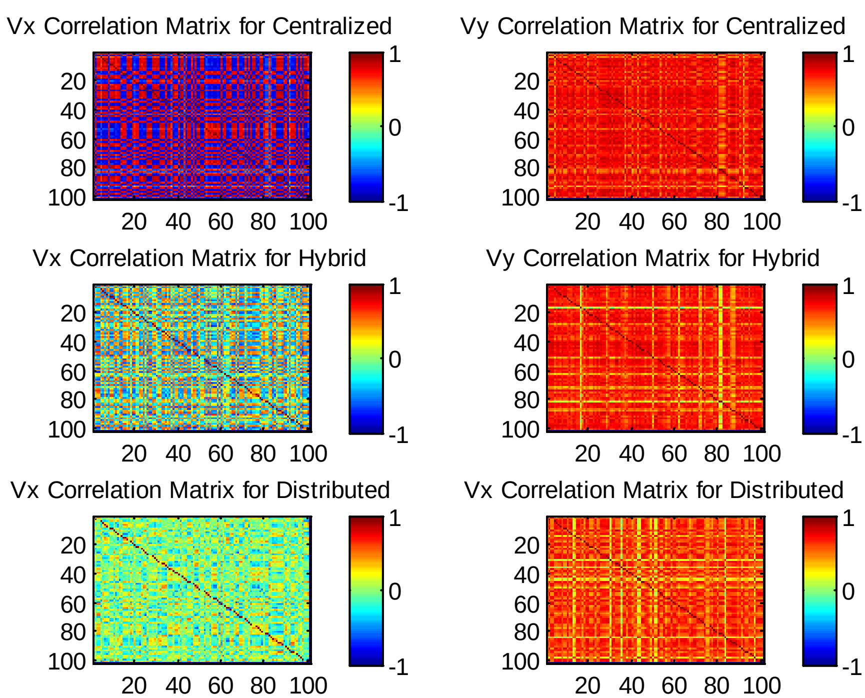

Figure 19 Speed components correlation for the "Avoid" scenario.

In the next step of the "Avoid" scenario analysis, the spatiotemporal method was used. The three categories differentiate in their spatial structures significantly, as shown in Figure 20. The centralized case showed a large dispersion of populated cells. In other words, the structure exhibited low density. Both the hybrid and distributed case showed tighter formations with lower dispersion and higher density. The distributed case showed the highest density, as different agents selected the same route based on local information. This finding related to the characteristic of self-organized phenomena of creation of spatiotemporal structures out of a homogenous pattern. The distributed case was the best display of a self-organized swarm (based on each agent with no global information).

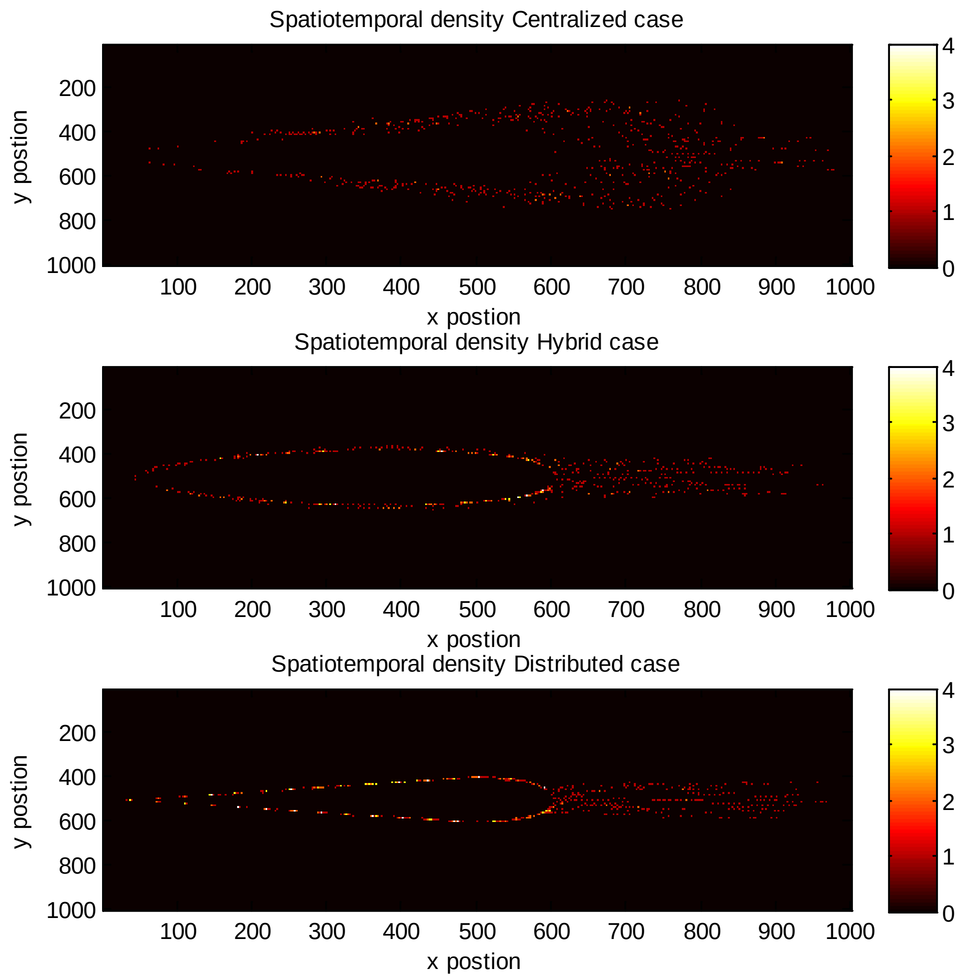

Figure 20 Spatiotemporal density for the "Avoid" scenario.

Next, the swarm normalized spatial entropy measure over time for the "Avoid" scenario was compared for the three categories. The entropy plots are shown in Figure 21. The distributed and hybrid cases that show early, defined, dense spatial-structures exhibit earlier decrease in entropy. Eventually, all categories converge to similar entropy values, as the scenario ended when all agents reach the final destination.

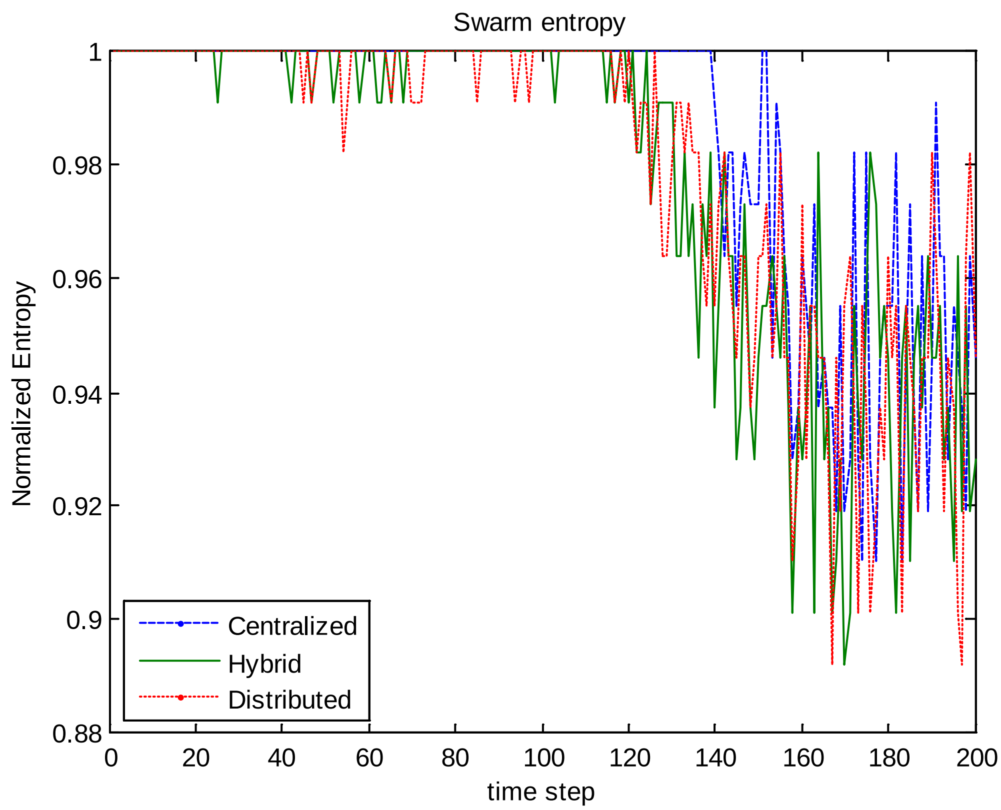

Figure 21 Spatial entropy over time for the "Avoid" scenario.

Figure 22 displays the fractal dimension plots for each time step. Again, the scale of 101 box size was used as the scale in which our swarm exhibits some measure of fractal properties. The right column plots showed similar variability over time of the local dimensions in the three categories.

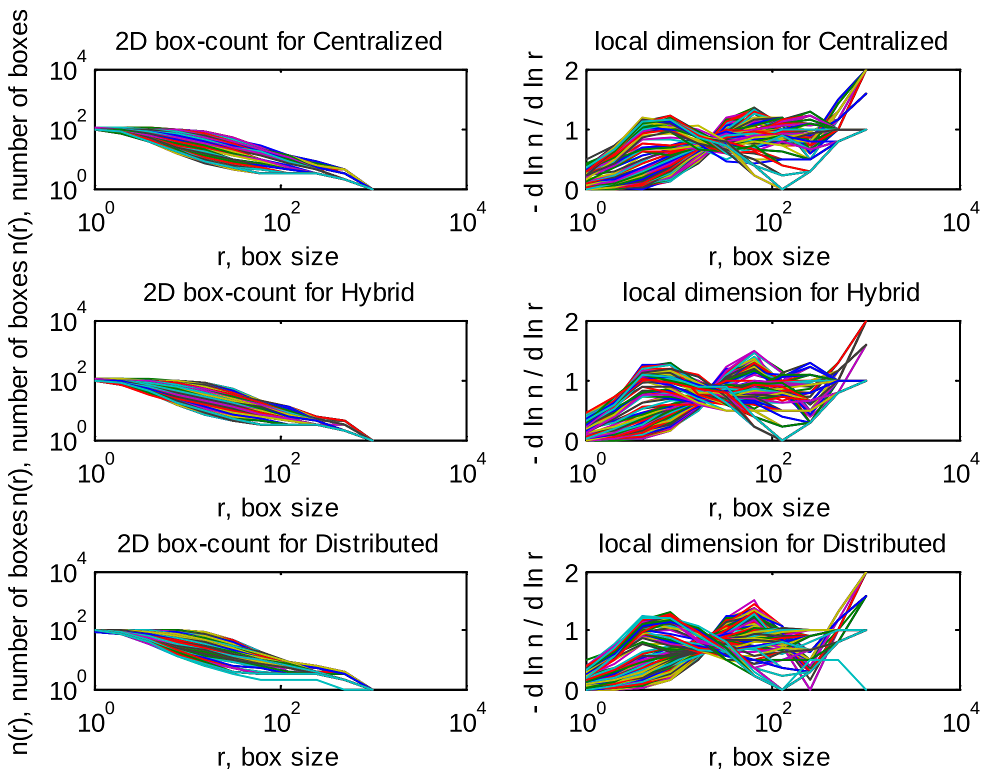

Figure 22 Box counts and local dimension plots for the “Avoid” scenario.

Examining the fractal dimension behavior over time in Figure 23 showed a similar behavior for the distributed and hybrid swarms (in accordance to the entropy measures). Both categories exhibit a “step” form that related to the shift of these swarms from dispersed formation to well defined curves (closer to a line in space). The centralized swarm showed gradual and continuous change of dimension, which related to the slow convergence of the centralized swarm toward the final destination.

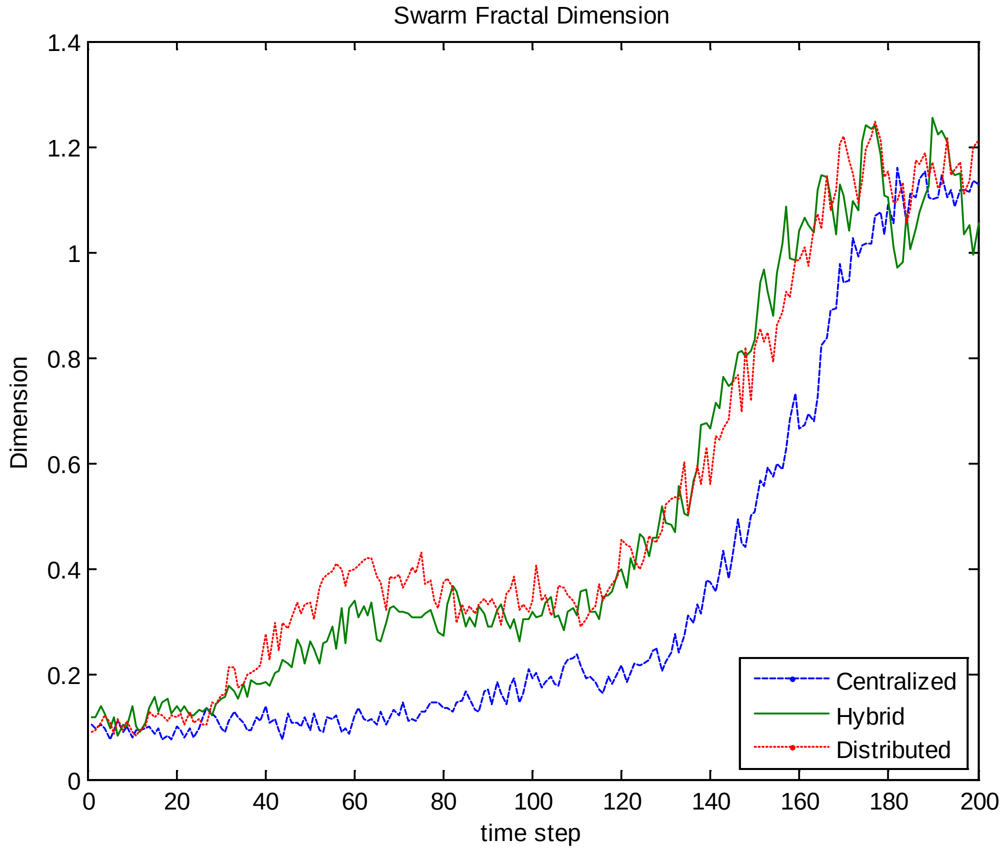

Figure 23 Fractal dimension over time for the "Avoid" scenario.

Figure 24 shows the resulting potential figure with the inherent assumption of a radial point-source field. While this approach proved accurate for the centralized "Rally" scenario, as all agents were attracted to the center mass of the swarm, in this case, an additional field source (the enemy unit) was taken into account. The resulting color map did not convey this information appropriately. As a reminder, the final location for each agent was assigned a minimum value of zero and all other values were simply assigned a value based on distance. That assumption related to a $\phi \propto kr$ potential form, which came from the constant force (of attraction) exerted by objects in the MANA simulation (i.e., force of attraction is range-independent and constant as long as the object of interaction was inside the agents' sensor range).

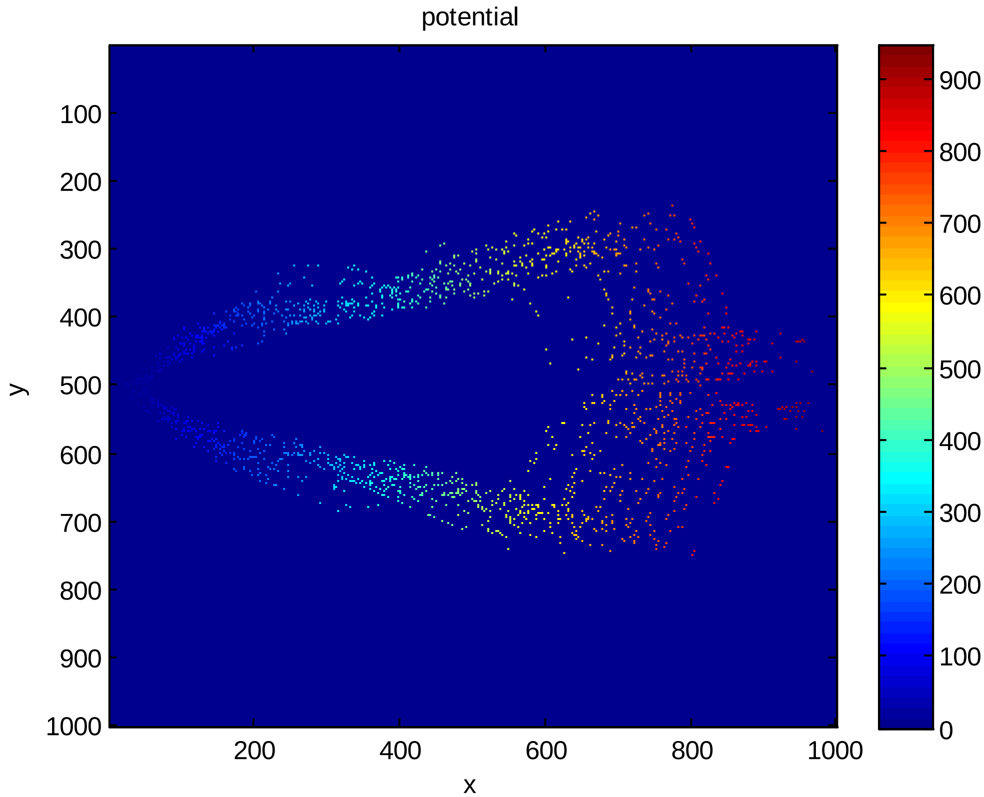

Figure 24 Potential display for the centralized case in the "Avoid" scenario.

c. *Summary of Differentiating Information Sources Analysis*

In this section several methods have been used to differentiate among information source types by looking at the emerging swarm movement patterns. From microscopic agent analysis, different agent routes geometries and speed correlation to other agents was observed. Hybrid agents displayed curved routes as a result of a combination of forces operating in the agents' decision making mechanism. As the agent's decisions were more based on a global source, a higher speed correlation was observable.

From the swarm collective system perspective, spatiotemporal structures displayed higher density as the swarm increasingly relied on local information sources. Spatial entropy over time related mostly to clustering characteristics of the swarm movements. As these clustering patterns differentiated between information source categories, so did the descriptive entropy plots. Finally, the fractal dimension of the

swarm over time proved to show interesting description of both the clustering transitions and the dimensionality of the patterns (i.e., points versus lines versus planes). The distributed and centralized fractal dimension plots gave extreme upper and lower boundaries for both the slope and absolute value of the hybrid category.

In general, it seemed that as real-world swarms may implement some form of hybrid information sources for their decision making process, metrics based on speed correlation, spatiotemporal structures density, entropy and fractal dimension slopes could be used. We have seen that all of these measures showed that the hybrid case displayed values inside the bounded range of both extremes. As the hybrid implemented in these test cases was perfectly balanced, a different weighting ratio was possible. By anchoring the absolute values of the distributed and centralized extreme cases for each of these metrics, a range of values was established. Then, by noting where the observed unknown hybrid swarm value fell within that range, we mapped that value to the underlying weighting ratio in the swarm agents' control mechanism.

2. Identification of Integration in the Swarm

The framework shown in Table 4 focuses on different information sources and interaction types. The next step was to look at the additional dimension of that framework which related to integration levels implemented by the swarm. As a reminder, the implementation of integration in MANA was done using trigger states to display change in agents local rule sets in accordance to other agents changed traits.

In order to analyze the different characteristics of the swarm, the "Rally" scenario was implemented again, only this time dubbed as "Rally integration." The distributed and centralized control mechanisms measures were compared to the measures of the integrated swarm.

The integrated swarm was simulated by using a trigger state. The integrated swarm's default state was identical to the distributed swarm. Once the integrated agent reached within a range of 2 meters from another agent, it interacts ("fuels" in MANA lingo) with that agent, thus triggering a new state. The new trigger state was that of a centralized swarm. The personality weights for that scenario are shown in Table 7.

Category name	Information source	A.K.A	Personality property	Agent SA	Squad SA
1. Local	Local	"Distributed"	Attraction to other swarm agents	10	0
2. Global internal	Global	"Centralized"	Attraction to other swarm agents	0	10
	Local	"Integrated" (**default state**)	Attraction to other swarm agents	10	0
	Global	"Integrated" (**trigger state**)	Attraction to other swarm agents	0	10

Table 7. Personality weights for the "Rally integration" scenario

The unfolding of the “Rally integration” scenario for all three categories is shown in Figure 25:

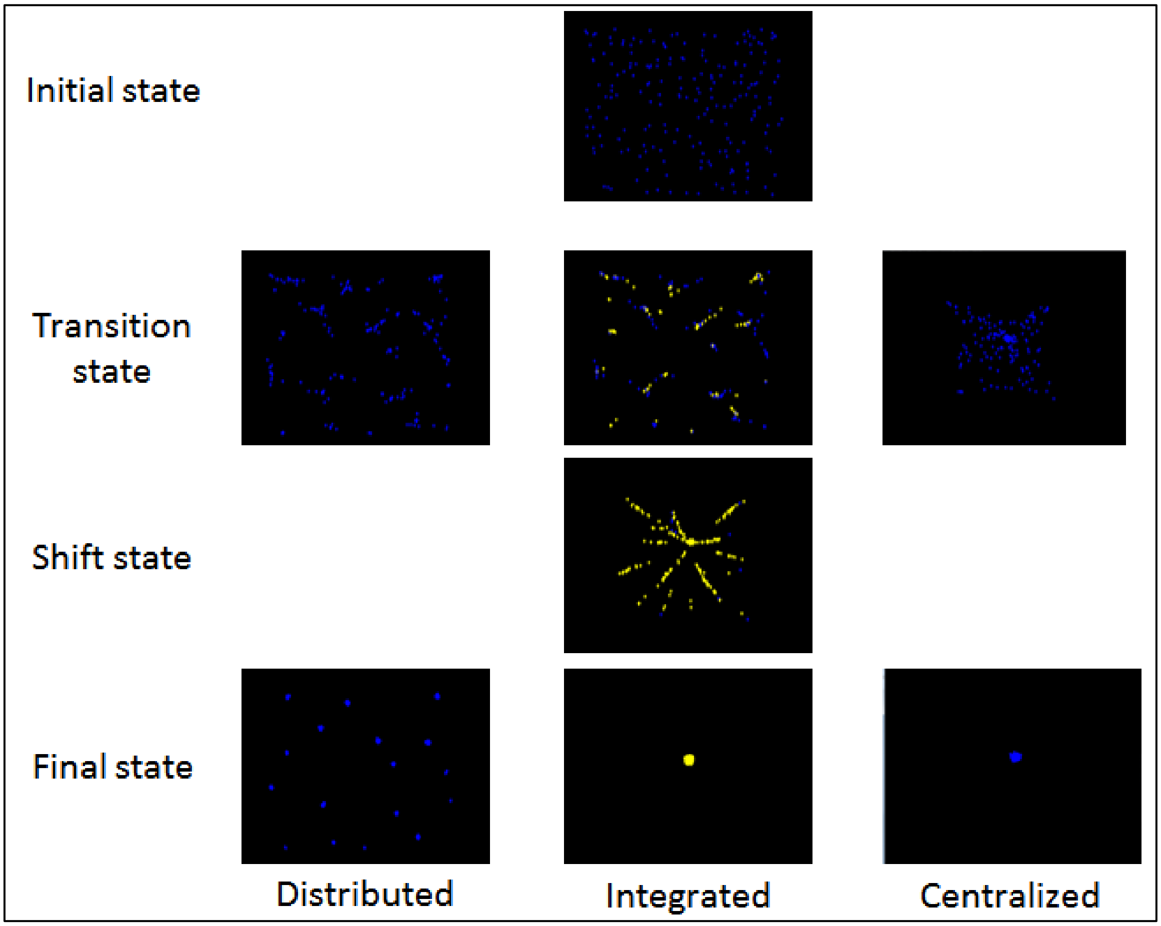

Figure 25 MANA frame shots of “Rally-integration” scenario

The movement patterns of the distributed and centralized categories shown in Figure 25 are known from the “Rally” scenario. The middle column depiction of the integrated swarm pattern is different. The yellow color highlights the swarm agents that have been “triggered.” The agent color was simply a debugging tool for the researcher and had no effect on the scenario outcome. In the transition and final states the integrated swarm displayed similar patterns to those of the distributed and centralized swarms respectively. So, the integrated swarm did not demonstrate new behavior as it was deep into one of its behavioral states. The interesting portion was the shift state – what

patterns emerged in the shift phase between to behaviors. In Figure 25, we can see a different unfamiliar pattern of several columns "lunging" at the center mass of the swarm.

The comparison analysis between the integrated swarm and the two element categories composing it was performed using some of the methods shown in the previous section. The system approach to the integrated swarm comparative analysis proved more effective. In Figure 26, the spatiotemporal structure of the integrated swarm was compared to the two basic categories.

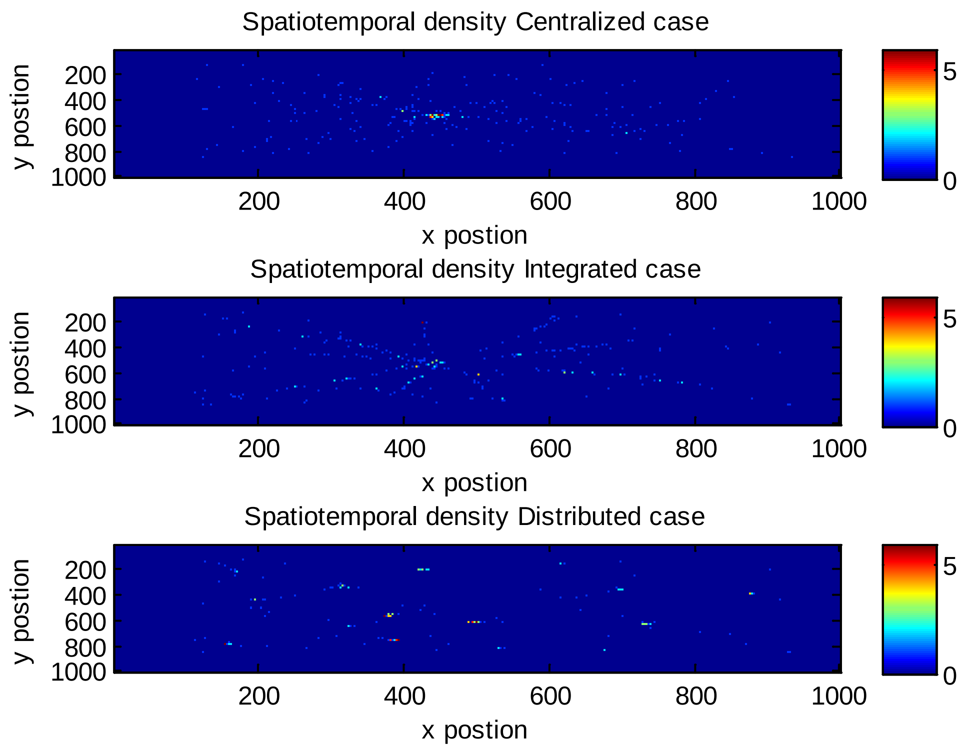

Figure 26 Spatiotemporal density of the "Rally-integration" scenario.

As seen in the hybrid case (in the Rally scenario) the integrated swarm shows column structures of higher density. In contrast to the hybrid swarm, which had curved lines, the integrated swarm has straight columns. This can be explained by the chain of events. The integrated swarm started out as a distributed swarm "drawn" to create localized clusters. Once agents met in these clusters, they triggered each other to the

centralized state, thus gaining access to the global information source which attracts them to the center mass. In contrast to the clusters in the hybrid case, the integrated clusters broke down immediately after the trigger, as there was no conflict with the local information source as that source has been forfeited.

Next, the integrated swarm spatial entropy was compared to the two basic categories, as shown in Figure 27. The integrated swarm entropy started out initially as the distributed swarm. As the trigger was activated, the integrated swarm's entropy shifts quickly to a downward slope and eventually reached that of the centralized swarm.

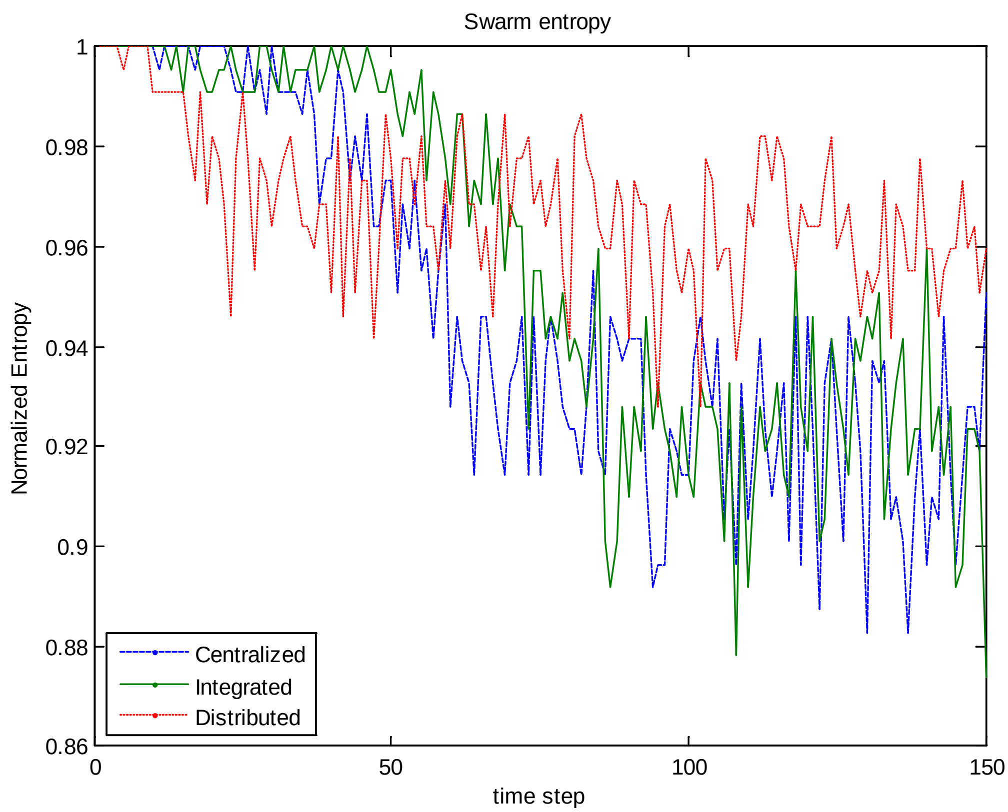

Figure 27 Spatial entropy over time for the "Rally-integration" scenario.

The local dimension and the log-log plots of the box count algorithm in Figure 28 were used to build the plot of the integrated swarm's fractal dimension over time.

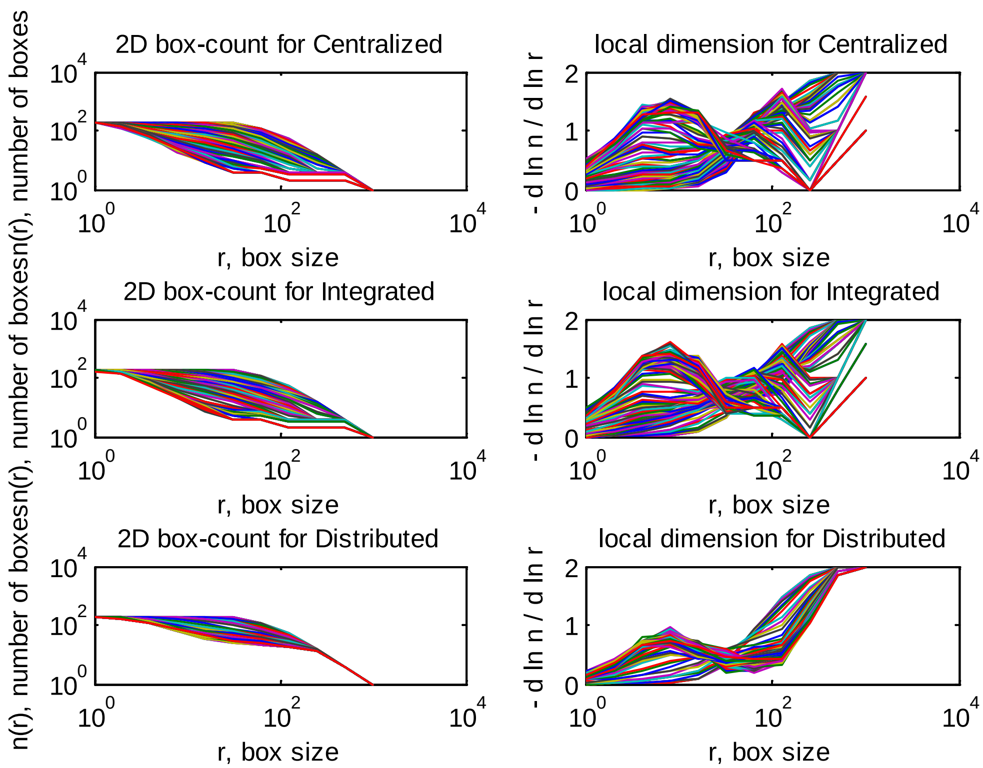

Figure 28 Box counts and local dimension plots for the “Rally-integration” scenario.

The fractal dimension plot over time of the integrated swarm started out initially with the same slope and values of the distributed swarm (see Figure 29). After the trigger was given (around t=10 seconds, when the local clusters form), the integrated swarm’s slope displayed the same behavior of that of the centralized swarm. After a while, its fractal dimension was identical to that of the centralized swarm. We can see that in contrast to the hybrid swarm that showed a “middle ground” between the basic categories which proved as a whole different behavior set, the integrated swarm’s fractal plot was basically composed of two portions each distinctively relating to one of its two basic category components. The shift stage (in the 10–40 seconds period) was the only portion that does show unique behavior

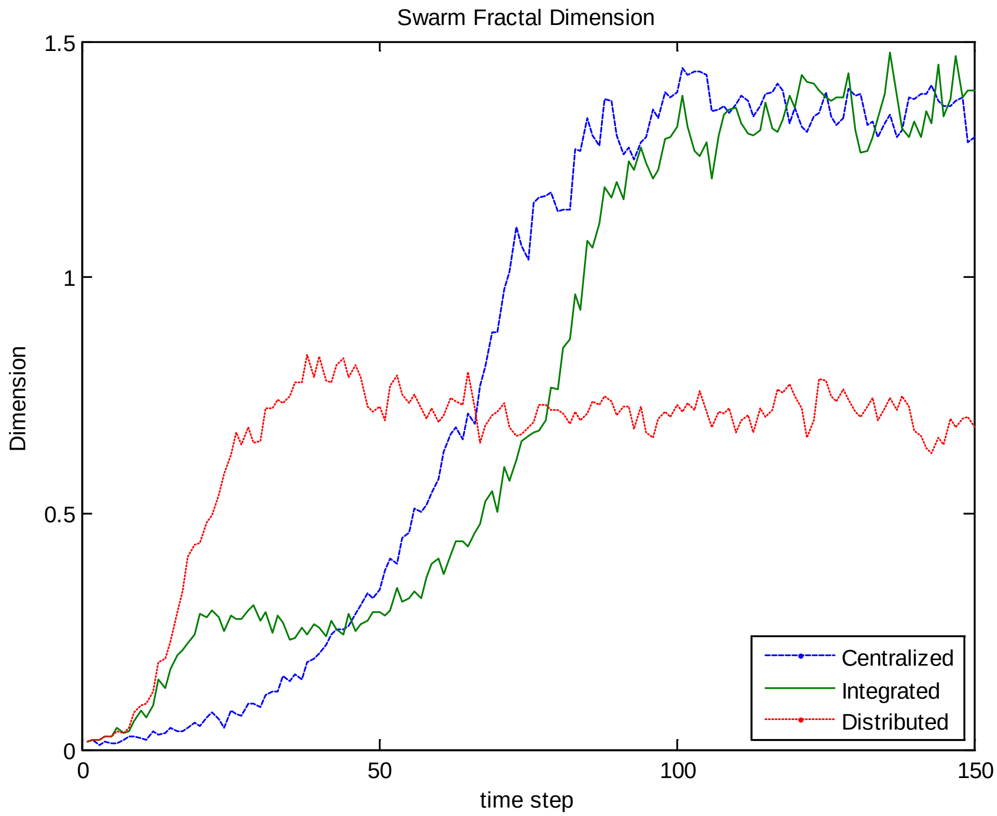

Figure 29 Fractal dimension over time for the "Avoid-integration" scenario.

The core insight to the detection of the presence of integration in the swarm was discovered in the system measure plots (e.g., entropy, fractal dimension). These plots showed integration of several basic behaviors into one plotted measure. In contrast to the hybrid conclusion where we saw an intermediate metric value / slope between the extreme behaviors, in the integrated swarm, we saw those behaviors comprising different portions in time of the same plot (with some shift phase between them). That insight helped identify the presence of integration by identifying that shift between behaviors with the discontinuity of the plot's derivative (i.e., the shift between behaviors was not smooth).

3. Distinguishing Controlled and Autonomous Swarm Agents

As discussed in Section C, control mechanisms of autonomous unmanned systems are characterized by the use of feedback control systems. It was assumed that a swarm agent interacting and responding to the existence of other swarm members displayed some fluctuation around a general trajectory (e.g., to maintain distance) due to these inherent characteristics of the feedback control mechanisms. These fluctuations differed from the case of a centrally controlled swarm, in which agents maintained formations by predefined stable trajectories. A way to distinguish the autonomous agent was based on the agents fluctuating speed behavior and thus did not require an approach comparing to other swarm members. By using a moving standard deviation (STD) of an agents' speed, a threshold was set for the STD that was considered as controlled. That is, if the agent maintained a speed STD lower than the threshold for a certain time period, it was considered to be externally controlled. The window used for the moving STD calculation was long enough to assure speed was indeed maintained, but not too long to allow for the case of direction change in a controlled agent.

In Figure 30, an agent's moving-STD-of-speed plot taken from the "LOS command source" scenario (discussed in the next section) is shown. The STD is computed for the *x* direction speed component. The selected STD threshold for the scenario was 0.5. This number was selected as MANA's cell based speed calculations tend to exhibit these fluctuations when an agent was moving in a diagonal (i.e., not parallel to one of the axes). The minimal amount of time defined for the agent to maintain this threshold to be considered "centrally controlled" was 20 time steps (20 seconds). The moving window for the STD calculation was set to 15 seconds. These definitions are relevant for the MANA simulation environment and did not relate to realistic numbers. So, in the case shown in Figure 30, the agent displayed "controlled" behavior in the ~20–72 seconds time period.

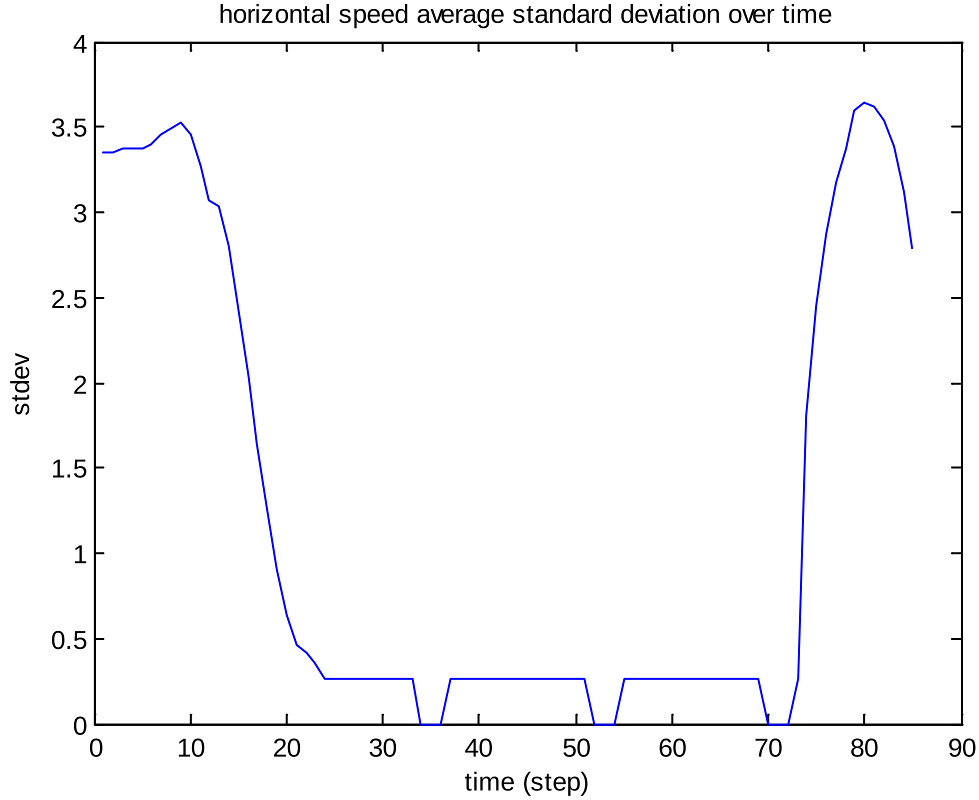

Figure 30 An agent's x direction speed moving STD

4. Triangulation of LOS External C2 Unit Location

After establishing a method to detect whether a swarm was controlled by an external C2 unit, there were cases in which that C2 unit was in close range (e.g., LOS for control channel). In such a case, it was possible for the defender to triangulate the source of the swarm control unit by observing the swarm's movement patterns. The point in time in which an agent had transitioned from autonomous mode to controlled mode was established via the method described in Item 3. Given an agent's transition, we established that the agent had been given an external command and thus had entered the range of the control unit at that moment or with some command lag.

a. LOS Command Source Scenario Assumptions

For sake of simplicity and the MANA limitations, some assumptions regarding the triangulation in the "LOS command source scenario" were made:

- The agent was given the command as he crossed into the limiting range of the control unit. Despite that simplifying assumption, there was still possible lag between the time of command and the observable transition (due to processing, inertia moments and so on). Inertia moments were actually taken into account in MANA and therefore, depending on the agents speed (direction and magnitude) at time of command, different time delays were experienced.
- The command unit control range of the swarm was smaller than the swarm spread area. (i.e., swarm agents were moving outside of control range and entering it – a difference in trajectories was observable through a change in rule set triggered by the command unit).
- The command unit was assumed to move substantially slower (static for our purposes) than the swarm.

b. LOS Command Source Scenario Description

The scenario began with agents placed randomly inside the square perimeter, as shown in Figure 31. The agents began moving randomly with a 10 meter defined average random path length (λ in the exponential distribution). As an agent crossed within a 100 meter range from the command source (as shown in Figure 32), the command unit interacted with the agent by triggering it into a controlled mode that directed him to the waypoint at the left of the battlefield, as shown in Figure 33. The agent's direction was set at this point and the random fluctuations cease. In reality the C2 unit, the interaction lines and the highlighted "controlled" agents were not observable. To convey this notion, and the difficulty of distinguishing a C2 presence, Figure 34 shows how Figure 33 would look without any of the "debugging" helpful highlights.

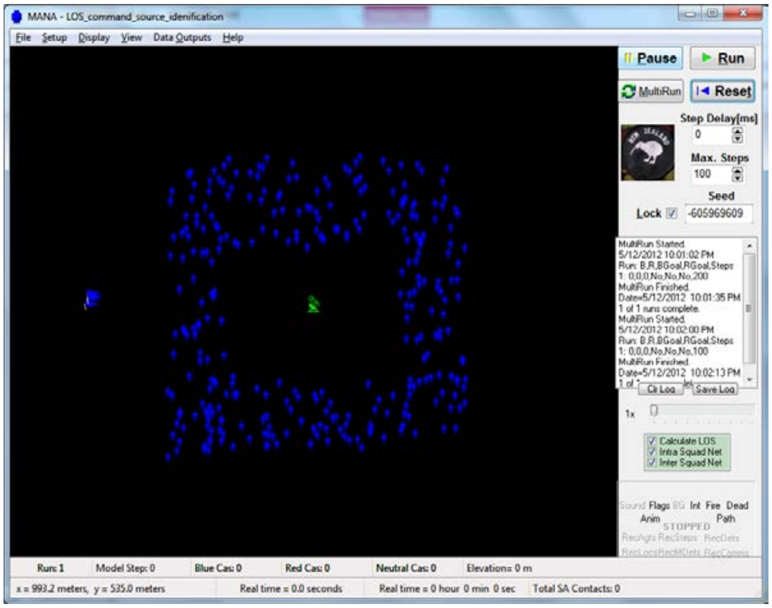

Figure 31 LOS command source scenario – initial conditions

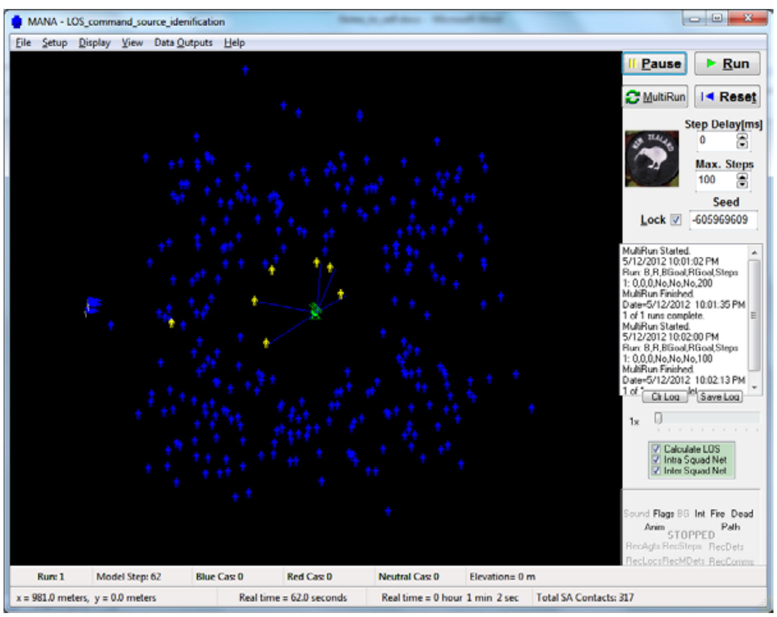

Figure 32 LOS command source scenario – C2 interaction and agents' transition

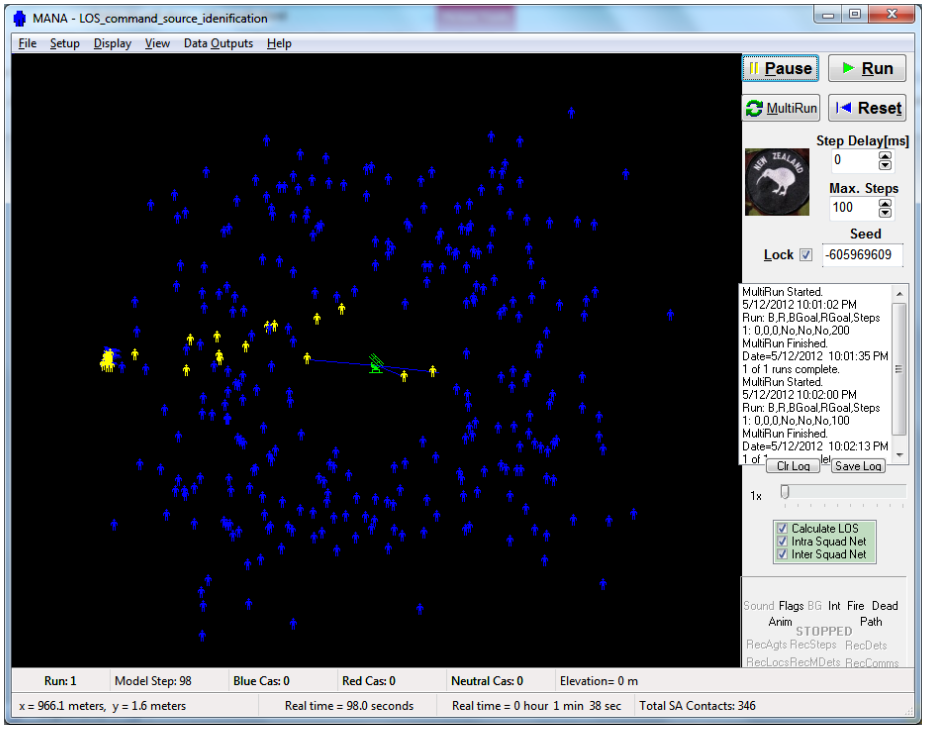

Figure 33 LOS command source scenario – agents' controlled movement to waypoint

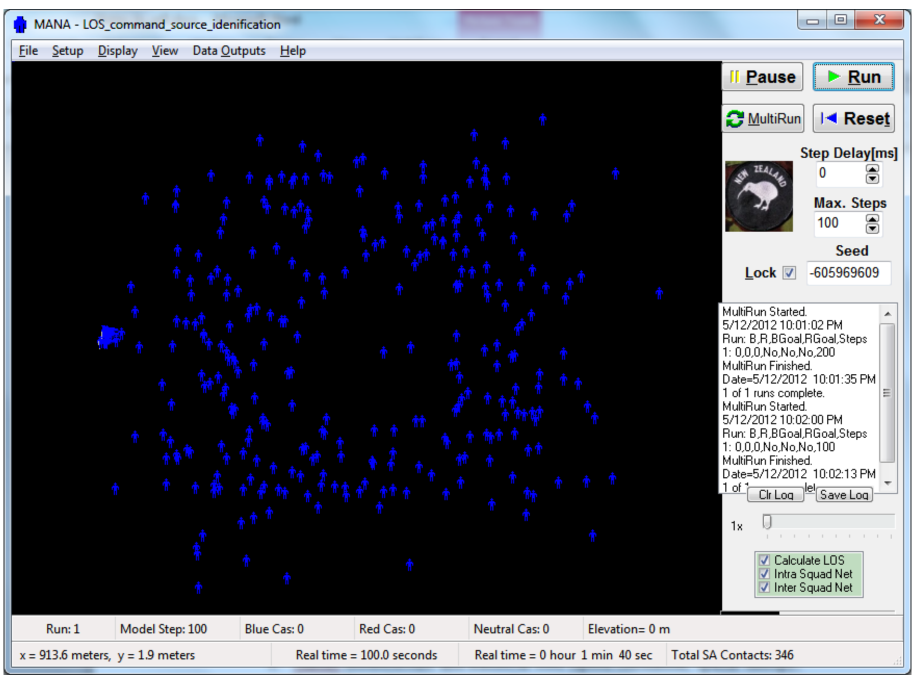

Figure 34 LOS command source scenario – without the highlights

c. *LOS Command Source Triangulation*

The transition locations of several agents were used to triangulate the source of command by applying the constraint that states all transitions must occur in the specified limiting range. For every possible command source location in space a value was given according to an objective function. The objective function utilized a matrix O, where Oij = (range from Agent *i* to the possible command source location) - (range from Agent *j* to the possible command source location). The objective-function was the sum of all the matrix elements. By searching the minimum (optimum) of the objective-function, the difference in estimated ranges decreases. In a perfect situation, the objective function would reach zero when all ranges were equal (i.e., the case of a perfect circle as transition locations and the estimated command source in its center).

In Figure 35, the surface color map shows the objective-function value for each point in space. We can see that the minimum value for the objective function in this case was around 20,000 dividing by n^2 (where n is the number of commanded agents in this scenario) gives us 20,000/1,444=13.85 which is the mean difference between two agents in estimated ranges from the command source. The minimum value, and therefore, estimated C2 unit location, is marked by a red dot. The actual C2 unit location is marked by the small green *x* mark. The commanded agents' locations at the time of observable transition to commanded mode (by the speed STD method described in the previous section) are marked by small blue circles. These locations were the basis for the objective function calculation.

Figure 36 shows the ranges distribution from the C2 unit to each agent's commanded-location. The distribution was based on the estimated C2 unit location from the triangulation Figure 35. As stated previously, in a perfect circular arrangement this distribution would just show one "delta" function located exactly on the 100m true value.

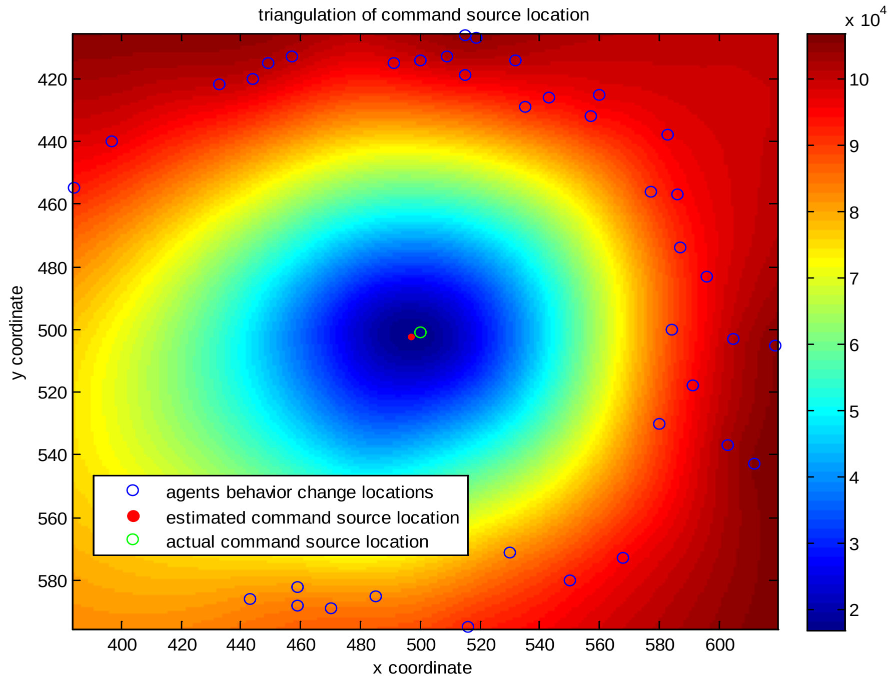

Figure 35 LOS command source triangulation

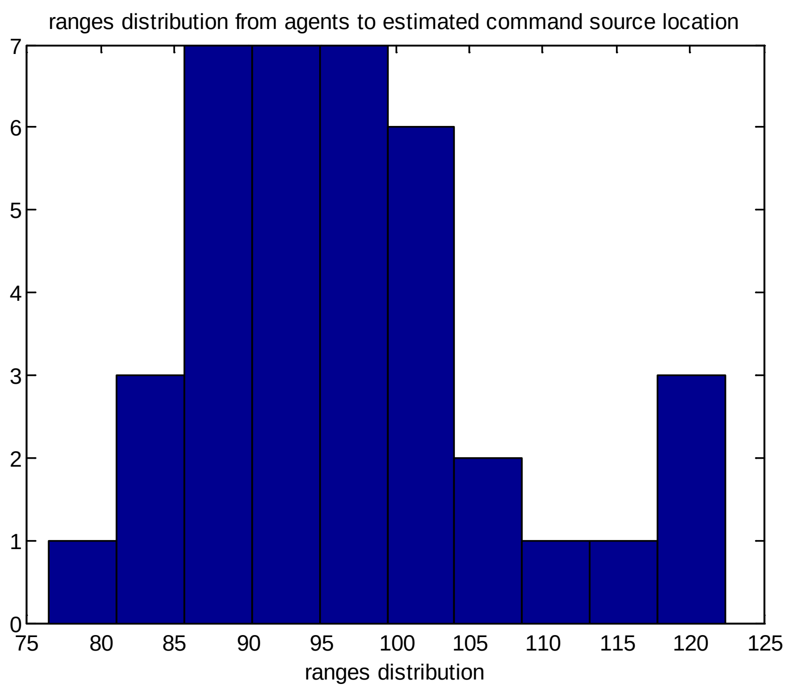

Figure 36 Estimated ranges distribution for the C2 unit

Obviously, the minimum solution was not perfect due to different lag times. For further optimization, the algorithm looked into past locations (assuming a common lag) to find when the STD of the estimated ranges distribution was the smallest, corresponding to the "true" commanded locations. The analysis showed that this method corresponded to the minimum error from the actual source location. This relationship between the estimated location error and the STD of estimated ranges can be seen in Figure 37. The optimal time delay in this case was zero. Meaning the original observable transition moment should be used. As the STD of ranges decreased, so did the estimated location error.

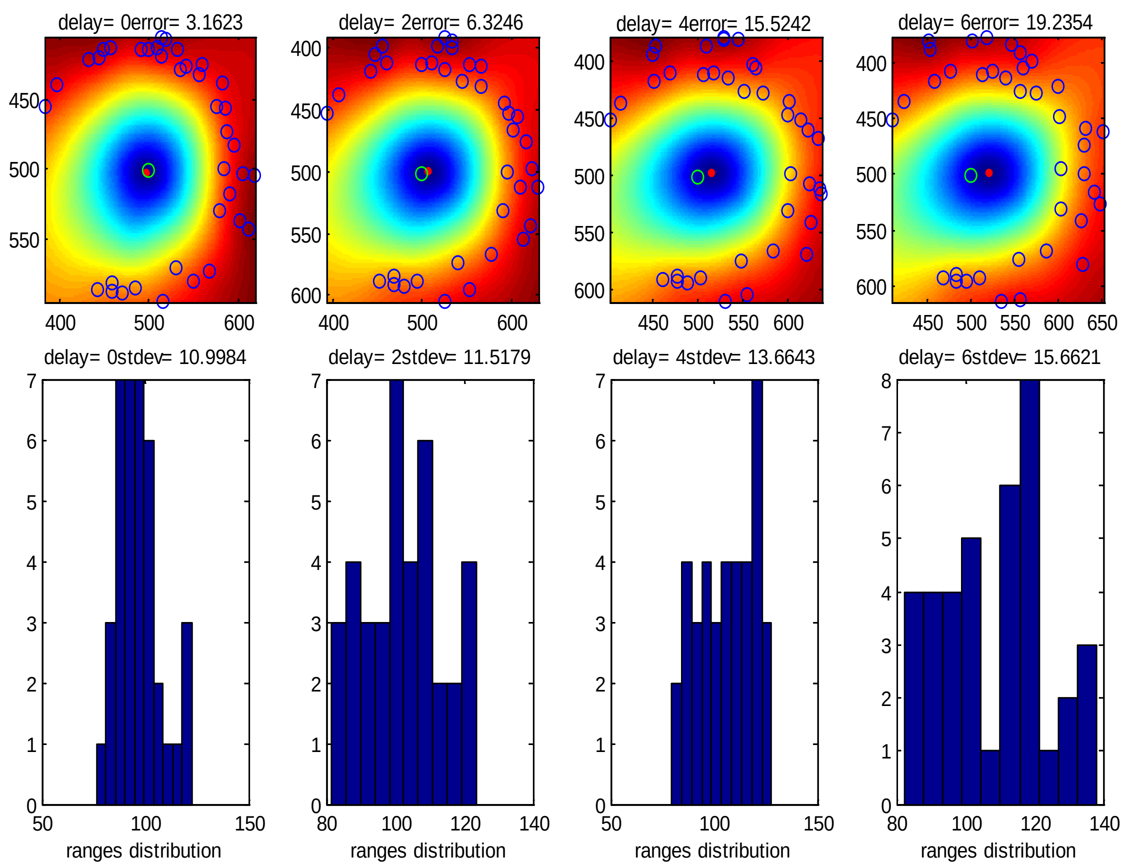

Figure 37 Command lag time, ranges STD and estimated location error relationship in the triangulation method of the LOS command source scenario.

In addition, the analysis showed that as the number of agents used for triangulation increased, the estimated location error decreased. The same LOS scenario was run (using the same random seed) for durations of 100, 200, and 300 seconds. As the simulation period increased, more agents were "commanded" and thus more data points were used for triangulation. The respective number of agents for the simulation times stated above was *n*=10, 28 and 47. Each row in Figure 38 showed a different duration (and thus number of agents). Top = 10 agents, middle = 28 agents and bottom = 47 agents. The columns corresponded to different time delays that were explored.

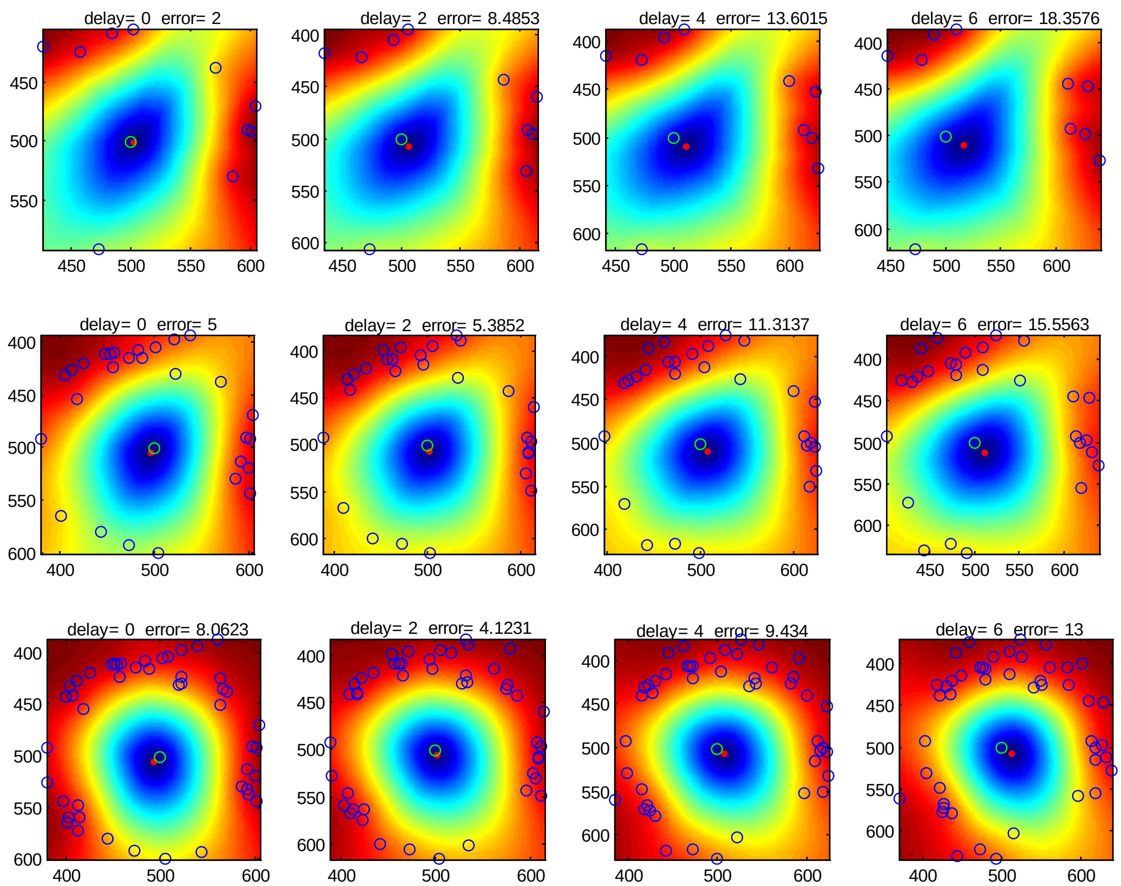

Figure 38 Effect of number of observed agents on triangulation accuracy.

Comparison of the error values for the three right columns showed that as the number of agents increased, the triangulation error decreased (with diminishing returns on additional agents). The left column does not comply with that trend. The explanation found for this phenomenon was that using a general time delay for all agents was too crude. In reality

(and in the simulation) each agent experienced a different lag based on its own speed at the time of command. Therefore, it may be possible to see that adding agents for a wrong time delay (for those agents) might result in decreased accuracy. A fully optimized triangulation algorithm would allow for different time delays between agents until the minimum range STD is received, which would comply with the actual command times. This algorithm enhancement was not performed in the scope of this research, but could be an interesting optimization of the current method.

Figure 39 shows the ranges histogram distributions for each of the respective columns and rows in Figure 38.

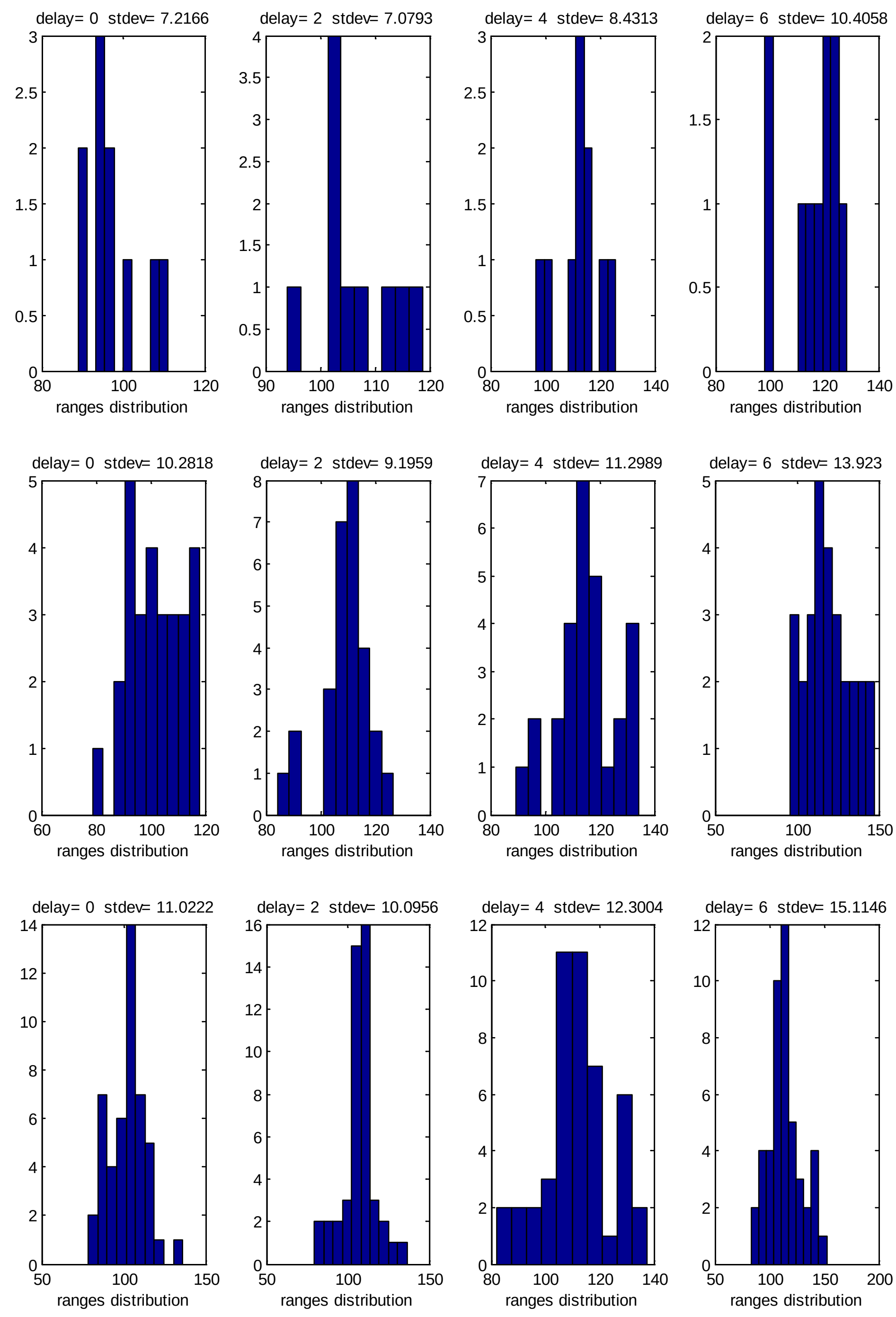

Figure 39 Effect of number of observed agents on estimated ranges distribution

In a sense, the dependence of estimation accuracy on swarm numbers is linked to the collective intelligence concept discussed by researchers discussing theories of swarms. In a way similar to what was discussed with the concept of collective intelligence, in our analysis, we exploited the swarm's collective information to gain a better estimation of the command unit location. The swarm, by sheer numbers, corrected our inherent inaccuracy (due to unknown time delays) by having there be an average of the estimations. So the basic property of the swarm that gave it scalability and robustness was turned against it.

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VIII. CONCLUSION AND RECOMMENDATIONS

A. CONCLUSION

The interpretation of the swarm movement patterns from the analysis of the MANA agent-based simulation showed the ability to differentiate the selected control mechanisms, based on several methods:

- Swarm agents speed correlation measure.
- Formation of spatiotemporal structures (in space over time) with varying density and dispersion by agent positional data.
- Change in the swarm's spatial entropy measure over time.
- Change in the swarm's fractal dimension behavior over time.

A possible mapping method of these measures back to the underlying weighting preferences of the swarm agents is suggested for further study. It is emphasized that in reality, most swarms would implement hybrid control mechanisms, based on local and shared information sources. These hybrid-swarms' underlying preferences could be mapped by their relative behavior with respect to the bounding centralized and distributed extremes.

In addition, the integrated swarm displayed a unique "shift phase" between behaviors which would help identify the presence of integration due to discontinuity in the system-measures (e.g., entropy and fractal dimension) derivative.

Lastly, triangulation of the swarm C2 source feasibility is displayed, with inherent accuracy limitations. Initial accuracy improvement studies show dependence on:

- Number of swarm agents used for estimation.
- Ability to compensate for command lag through exploration of different time delays from recorded positional data.

This thesis concludes that the proposed observational approach would allow mapping of an observed behavior into a category (group) of rule sets (control schemes). This mapping of swarm control-mechanism categories would be established from the

integrative model and would be categorized by their information source, interaction type and level of integration. Additional knowledge such as the swarm's C2 unit location, and communication range constraint might be established by utilizing observed movement patterns data. It is suggested that further study of the proposed observational system would contribute to a qualitative understanding of the opponent swarm, thus contributing to the selection and effectiveness of counter-measures.

B. RECOMENDATIONS FOR FURTHER STUDY

1. Open Research Questions

- Will an artificial "observation" system be able to notice the differences in these complex behaviors? (i.e., with no man in the loop)
- Can the complex emergent behavior be mapped back to a single local rule set? Or are there many possible input rule sets that result in the same complex behavior?
- In reality tactical swarms may include heterogeneous agents with different internal control mechanisms. How would the suggested observational system perform with respect to such heterogeneous-swarms?
- How would partial availability and errors in recorded position data effect the performance of the suggested observational system?

2. Options for Further Analysis

Research using agent based models and the previous analysis based on statistical methods, physics based concepts and optimization has proved fruitful. During the course of the analysis, several additional opportunities have been discovered:

- Establishing inter-communication range constraints between swarm agents based on local interactions and changes in agents' movement patterns. (After establishing the existence of a global internal information source). This research could follow similar steps taken in the triangulation of a C2 unit. Another option would be to identify a "chain-reaction" such as seen in force chain-reactions in crowds. By identifying the spatial period of the "wave" moving within the swarm pattern, the limiting communication range might be detected.
- Further optimization of the triangulation error of a LOS C2 unit. As discussed in the analysis, each swarm agent experiences a different command lag. By using an exhaustive search algorithm through all possible lag combinations for different agents an accurate estimation may be possible. In reality, SNR in combination of a 3D environment will also make the range assumptions much more complex. This research option is not suitable for agent-based modeling.

- Mapping hybrid swarm's underlying decision weights to values in the system measure plots. This research option has been elaborated on in the analysis' conclusions.
- Mapping swarm field potentials. Self-organized phenomena have a basic characteristic of several stable states. This research hypothesized that while agents move through space over time, their combined trails may help identify global or local potential fields. Given sufficient agents moving in space these fields can be "drawn" with sufficient resolution to unveil local and global attractors and repellents of the swarm collective. Initial work has been made in the scope of this research, but one of the limiting factors for the method used was that at any given moment in time an agent's trajectory is established based on its local sensor. Therefore, the perceived "potential" fluctuates not due to actual changes in the environment but due to changes in the agent's perception. This limitation obviously varies based on the agent's information source and sensor range.

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